MAGICC/SCENGEN 5.3: USER MANUAL (version 2)

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TERMS OF USE

Users of the MAGICC/SCENGEN software are bound by the UCAR/NCAR/UOP “Terms of Use”. For details see …

http://www.ucar.edu/legal/terms_of_use.shtml

1. Installation:

MAGICC/SCENGEN comes complete as a zipped set of directories (folders), SG53.zip. In unzipping, when asked where the folders and files should be extracted to, select C:\. Unzipping will create a new top level folder, C:\SG53, and all folders and files will automatically go into this folder. It is important that the new SG53 folder should be created directly under C: -- i.e., as C:\SG53.The full directory structure is shown in the flowchart at the end of this document.

2. Introduction – background

MAGICC/SCENGEN is a coupled gas-cycle/climate model (MAGICC; **M**odel for the **A**ssessment of **G**reenhouse-gas **I**nduced **C**limate **C**hange) that drives a spatial climate-change **SCEN**ario **GEN**erator (SCENGEN). MAGICC has been one of the primary models used by IPCC since 1990 to produce projections of future global-mean temperature and sea level rise. The climate model in MAGICC is an upwelling-diffusion, energy-balance model that produces global- and hemispheric-mean temperature output together with results for oceanic thermal expansion. The 4.1 version of the software uses the IPCC Third Assessment Report, Working Group 1 (TAR) version of MAGICC. The 5.3 version of the software is consistent with the IPCC Fourth Assessment Report, Working Group 1 (AR4). The MAGICC climate model is coupled interactively with a range of gas-cycle models that give projections for the concentrations of the key greenhouse gases. Climate feedbacks on the carbon cycle are therefore accounted for.

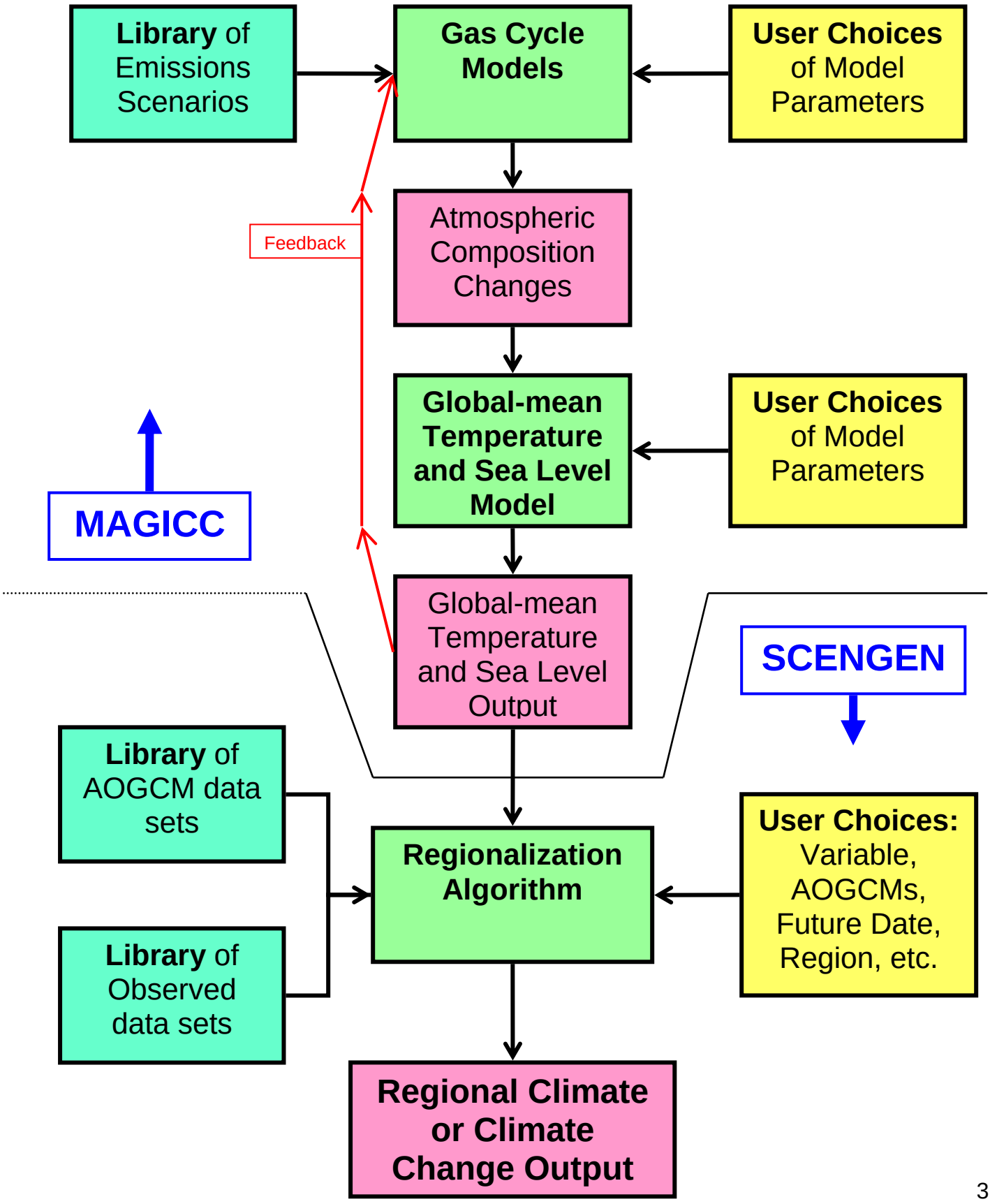
Global-mean temperatures from MAGICC are used to drive SCENGEN. SCENGEN uses a version of the pattern scaling method described in Santer et al. (1990) to produce spatial patterns of change from a data base of atmosphere/ocean GCM (AOGCM) data from the CMIP3/AR4 archive. The pattern scaling method is based on the separation of the global-mean and spatial-pattern components of future climate change, and the further separation of the latter into greenhouse-gas and aerosol components. Spatial patterns in the data base are "normalized" and expressed as changes per 1^{o}C change in global-mean temperature. These normalized greenhouse-gas and aerosol components are appropriately weighted, added, and scaled up to the global-mean temperature defined by MAGICC for a given year, emissions scenario and set of climate model parameters. For the SCENGEN scaling component, the user can select from a number of different AOGCMs for the patterns of greenhouse-gas-induced climate.

The method for using MAGICC/SCENGEN is essentially unchanged from the year-2000 version (Version 2.4; Hulme et al., 2000). What has changed is the MAGICC code (2.4 used the IPCC SAR – Second Assessment Report – version of MAGICC), the data base of AOGCMs used for pattern scaling, and the much greater number of SCENGEN output options open to the user.

As before, the first step is to run MAGICC. The user begins by selecting a pair of emissions scenarios, referred to as a Reference scenario and a Policy scenario. The emissions library from which these selections are made is now based on the no-climate-policy SRES scenarios, and includes new versions of the WRE (Wigley et al., 1996) CO_2 stabilization scenarios. The SRES scenarios have a much wider range of gases for which emissions are prescribed than was the case with the scenarios used in the SAR. Because of this, emissions scenarios can now only be edited or added to off-line, using whatever editing software the user chooses. The labels "Reference" and "Policy" are arbitrary, and the user may compare any two emissions scenarios in the library.

The user then selects a set of gas-cycle and climate model parameters. The default ("best estimate") set may be chosen, or a user set prescribed. Both default and user results are carried through to SCENGEN. A flow chart describing how MAGICC/SCENGEN is configured is shown on the next page.

STRUCTURE OF THE MAGICC/SCENGEN SOFTWARE


Library of Emissions Scenarios
Gas Cycle Models
User Choices of Model Parameters
Feedback
Atmospheric Composition Changes
Global-mean Temperature and Sea Level Model
User Choices of Model Parameters
MAGICC
Global-mean Temperature and Sea Level Output
SCENGEN
Library of AOGCM data sets
Library of Observed data sets
Regionalization Algorithm
User Choices: Variable, AOGCMs, Future Date, Region, etc.
Regional Climate or Climate Change Output

3. Modifications since version 4.1:

Version 5.3 has been modified extensively from the previous public-access version (4.1). The main changes in MAGICC are described first followed by the changes in SCENGEN.

3.1 MAGICC CHANGES

Forcing changes

Changes have been made to MAGICC to ensure, as nearly as possible, consistency with the IPCC AR4. In version 4.1, various forcings were initialized in 1990 (or 2000 in the case of tropospheric ozone), and subsequent forcings are dependent on these initializations. The version 4.1 initialization values were consistent with best-estimate forcings given in the TAR. In AR4, new best-estimate forcings have been given for 2005. This has meant that the 1990 initialization parameters had to be changed to give projected 2005 values consistent with these new AR4 results. As MAGICC includes historical values only to 1990 or (for CO_2) 2000, the 2005 values it produces depend on the chosen emissions scenario. Thus, it has not been possible to precisely emulate the AR4 2005 values. The differences, however, are very small, as will be shown at the end of this section. First, we give full details of the AR4 and MAGICC 4.1 forcings, followed by the forcing initialization changes employed in MAGICC 5.3.

***Table 1**: 2005 AR4 forcings (W/m^2) compared with forcings used for 1990 in MAGICC 4.1 or calculated for 2005 in MAGICC 5.3. In column 3, headed "AR4, 2005", the outer numbers give the 90% confidence interval, while the central (or sole) number gives the best estimate. In column 5, headed "MAG53, 2005", 2005 values are best estimate values and are scenario dependent. The range given is the best estimate range over the six SRES illustrative scenarios. Magenta is used to show forcings that are either the components of other forcings or component sums. Component sum comparisons for AR4 forcings (column 3) are shown in bold blue type. For example, items 11 through 16 are the components of 10 (total direct aerosol forcing). Summing the components (10a) gives a value slightly less than given in 10. Total forcing is given in row 21, which is the sum of 1, 2, 3, 4, 7, 8, 9, 10, 17, 18, 19 and 20. The sum of the individual components (21a) is slightly higher than the independent best estimate for the total (1.72 compared with 1.6).*

	COMPONENT	AR4, 2005[1]	MAG41, 1990	MAG53, 2005
1	CO2	1.49(1.66)1.83		1.645 to 1.661
2	CH4	0.43(0.48)0.53		
2a	CH4 + strat. H2O	0.55		0.524 to 0.528
3	N2O	0.14(0.16)0.18		0.165 to 0.167
4	Halocarb. direct	0.31(**0.34**)0.37		0.375
4a	1 + 2a + 3 + 4	2.71		2.711 to 2.731
5	Montreal gases	0.29(0.32)0.35		0.353
6	HFCs,PFCs,SF6	0.017		0.0216
4a	5 + 6	**0.337**		0.374
7	Trop. O3	0.25(0.35)0.65	0.35 (year 2000)	0.342 to 0.358
8	Strat. O3	-0.15(-0.05)0.05		-0.203
9	Strat. H2O from CH4	0.02(0.07)0.12		
10	Aerosol direct total	-0.1(**-0.5**)-0.9		
11	SO4 direct	-0.2(-0.4)-0.6	-0.3(-0.4)-0.5	-0.377 to -0.440
12	Fossil fuel organic C	-0.1(-0.05)0.0		See FOC (19a)
13	Fossil fuel black C	0.05(0.2)0.35		See FOC (19a)
14	Biomass burning	-0.09(0.03)0.15		0.023 to 0.025
15	Nitrate	-0.2(-0.1)0.1	Not included	
16	Mineral dust	-0.3(-0.1)0.1	Not included	-0.2 (items 15 + 16)
10a	Sum 11 through 16	**-0.42**		
17	Aerosol indirect	-0.3(-0.7)-1.8	-0.4(-0.8)-1.2	-0.674 to -0.743
18	Land use	-0.2	Not included	-0.2
19	Black C on snow	0.1		See FOC (19a)
19a	12 + 13 + 19 (=FOC)	0.25	0.1	0.230 to 0.269
20	Contrails	0.01		Not included
21	TOTAL	0.6(**1.6**)2.4		
21a	Component sum	**1.72**		1.596 to 1.673

[1] Ranges give the 90% confidence intervals. Values assumed to be mid-year values.

We now describe the forcing initialization changes. (All numbers are W/m^2.)

Tropospheric O3: Previously 0.35 was hardwired at the start of 2000. This gives a mid 2005 value averaged over the illustrative scenarios of 0.373 (0.362 to 0.378). 0.35 has been changed to 0.33. This leads to an error of less than 0.01 in 2005.

Biomass burning: Previously (in MAGICC 4.1) the value was -0.2 in 1990. The AR4 best estimate is +0.03 in 2005. If the1990 value is set to 0.03 in MAGICC, the 1990 to 2005 change ranges from +0.0035 to +0.0070 for the SRES illustrative scenarios (mean = +0.0053). We therefore change the 1990 initialization value to 0.025. For the 90% uncertainty range, we use the AR4 estimate of +/-0.12. (Previously used zero range.)

Fossil organic and black carbon: This is denoted by FOC in MAGICC. Previously, the 1990 value of FOC (FOC90) was set at 0.1. Now, if black C on snow is included, the value is 0.25 in 2005. If FOC90 is set to 0.25, the change over 1990 to 2005 ranges from -0.0139 to +0.0255 (mean = 0.0036). The average of the highest and lowest changes is +0.006. The 1990 initialization value is therefore set at 0.244. For the uncertainty range, the AR4 black carbon range of +/-0.15 is used (previously +/-0.1).

Nitrate: This was not included in MAGICC 4.1 and has now been added as a new aerosol forcing term (QNO3). The 1990 value is set at -0.1 (the AR4 best estimate) and QNO3 is kept constant at -0.1 after 1990 (based on small changes given in Bauer et al., 2007, and the fact that changes in nitrate aerosol require information about NH3 changes that are not available in the SRES scenarios). QNO3 is ramped up linearly from zero in 1765 to -0.1 in 1990.

Mineral dust: This was not included previously and is now added as a new aerosol forcing term (QMIN). The 1990 value is -0.1, and QMIN is kept constant at -0.1 after 1990 (based on the fact that changes are not available in the SRES scenarios – although one would expect them to be small). QMIN is ramped up linearly to -0.1 in 1990.

Stratospheric H2O: Previously this was 0.05*QCH4, which gives only 0.025 in 2005. The best AR4 value in 2005 is 0.07, with 90% confidence range of 0.02 to 0.12. We retain the TAR value, which lies within the AR4 uncertainty range.

SO4 direct and indirect: In MAGICC, aerosol forcing initialization values are specified for the year 1990. Modeled changes in both direct and indirect forcings are very small over 1990 to 2005, so we retain 1990 as the initialization year. Given the AR4 best estimate of -0.4 in 2005, the 1990 direct forcing can stay the same as in version 4.1 (-0.4). In accord with the AR4, the 1990 indirect forcing becomes -0.7 (previously -0.8). For uncertainty ranges we use +/-0.2 for direct forcing, the same as AR4 (previously +/-0.1). (This includes uncertainties in nitrate and mineral dust forcings.) For indirect forcing, we use +/-0.4 for the range, the same as previously. AR4 gives a range that is asymmetrical about the central estimate, -1.8 to -0.3. The -1.8 forcing value as a lower bound (1.1 W/m^2 below the best estimate) would lead to extremely low total historical anthropogenic forcing unless compensated by a large underestimate in some positive forcing term, and we consider this highly unlikely. We therefore retain +/-0.4 for the uncertainty range for indirect aerosol forcing.

In support of this decision we note that such a large negative indirect forcing for the lower bound would be inconsistent with detection and attribution (D&A) studies. Such studies to date have rarely considered indirect forcing explicitly, but they do so implicitly because the response

patterns of direct and indirect forcing are almost certainly similar. These studies give best estimate values of total sulfate aerosol forcing ranging from -0.1 to -1.7 W/m^2, with a mean of about -0.8 W/m^2 (Hegerl and Zwiers, 2007, p. 672). The lower bound here is much smaller in magnitude than the lower *a priori* uncertainty bound suggested by AR4. In addition, the central empirical estimate of -0.8 W/m^2 is noticeably smaller in magnitude than the combined direct plus indirect forcing of -1.1 W/m^2 (-0.7-0.4) given as the *a priori* best estimate in the AR4. We nevertheless retain the -1.1 value for initialization.

Although indirect forcing is defined and calculated specifically for sulfate aerosols, it is assumed to be a proxy for the sum of all indirect aerosol forcings.

Land use: This was not included in version 4.1. Since there are no standard projections we add this as another forcing (QLAND), constant from 1990 and ramping up linearly prior to this.

With these new forcing initializations, total forcing in the AR4 reference year, 2005, should be similar to the best-estimate of total forcing given in the AR4. As noted above, precise agreement is not possible as MAGICC's 2005 data are projections rather than specifically defined values. MAGICC values depend on the assumed emissions scenario. Nevertheless, the MAGICC/AR4 differences are very small, as shown in Table 2 below

Table 2*: Best-estimate total forcing in 2005 since pre-industrial times as produced by MAGICC 5.3. For comparison, the best estimate in the IPCC AR4 is 1.6 W/m^2.*

SCENARIO	**2005 TOTAL FORCING (ΔT2x = 3^{o}C) – W/m^2**
A1B	1.596
A1FI	1.610
A1T	1.673
A2	1.634
B1	1.615
B2	1.653
AR4	1.6

In the AR4, the best-estimate total forcing in 2005 is 1.6 W/m^2, with a 90% uncertainty range of 0.6 to 2.4 W/m^2. (Uncertainties are due primarily to uncertainties in indirect aerosol forcing.) Note that the component sum (Table 1) is slightly higher, 1.72 W/m^2, and the MAGICC 5.3 values lie between this and the best estimate total. While the MAGICC values are slightly above the AR4 best estimate total, the differences are miniscule relative to the overall forcing uncertainty and have virtually no effect on projections of temperature or sea level change.

Carbon cycle model and CO_2 concentration stabilization scenarios

Parameters in the carbon cycle model have been changed to give concentration projections consistent with the results from the C4MIP carbon-cycle model intercomparison exercise (Friedlingstein et al., 2006). In this exercise, the SRES A2 scenario was used as a test case. MAGICC projections for A2 agree with the average of the ten C4MIP model results, and the uncertainty range that MAGICC gives matches the 90th percentile of the C4MIP range. Further details are given in the Appendix below.

Because of changes in the carbon cycle and climate models, it has been necessary to modify the stabilization scenarios (WRExxx and xxxNFB) to ensure that the concentration profiles produced when these scenarios are run with default (best estimate) climate model parameters are the same as in MAGICC 4.1. This has been done for stabilization levels of 450 ppm upwards. For the 350 ppm stabilization case, the profile has been modified to use a later date of departure from the no-climate-policy (baseline) emissions scenario.

The baseline emissions scenario for these stabilization calculations has also been changed. In MAGICC 4.1 we used the P50 (SRES median) emissions scenario as the baseline and, for consistency, used the same scenario for non-CO_2 gases in all CO_2 stabilization cases. This is unlikely to be correct. If we are to introduce policies to stabilize CO_2 concentrations, then it is both cost-effective and consistent with the Kyoto Protocol that we should employ a multi-gas emissions reduction strategy. For any CO_2 stabilization scenario then, we should try to apply a consistent scenario for non-CO_2 gases. Attempts have been made to do this (Clarke et al, 2008), but, in the MAGICC context where the CO_2 scenarios are defined externally to follow WRE pathways, it is not possible to use fully consistent scenarios. Nevertheless, we do now use a stabilization scenario for non-CO_2 gases, but we use the same non-CO_2 gas scenario for all stabilization cases; namely, an extension of the MiniCAM Level 2 scenario given in Clarke et al. (more details are given in Wigley et al., 2008). This scenario includes emissions reductions for non-CO_2 gases that are consistent with a CO_2 stabilization target of 550 ppm. The emissions of non-CO_2 gases in the Level 1 (450 ppm stabilization), Level 2 (550 ppm stabilization) and Level 3 (650 ppm stabilization) are very similar. Although not perfect, this is a considerable conceptual improvement over MAGICC 4.1's use of P50 for non-CO_2 gases. Users can modify the emissions of non-CO_2 gases, of course, but (because this will change the magnitude of climate feedbacks on the carbon cycle) this will mean that the resulting CO_2 concentrations will stabilize at values slightly different from those that are produced by the original scenarios. Further details are given in the Appendix.

In addition, a new overshoot scenario has been added (450OVER) where CO_2 concentration rises to 540 ppm before falling to a 450 ppm stabilization level. This is the same overshoot scenario as used in Wigley (2006). 450OVER uses the same extended MiniCAM Level 2 scenario for non-CO_2 gases.

Sea level rise

In the IPCC Third Assessment Report (TAR; Church and Gregory, 2001), a new method was used for projecting sea level rise from GSICs (Glaciers and Small Ice Caps). This method was only meant to be used out to 2100 – if applied beyond 2100 (as, for example, in stabilization scenarios) it behaved quadratically, with sea level rise from GSIC melt rising to a maximum and then declining. Extended scenarios could therefore lead to large negative GSIC melt (i.e., a gain

in GSIC ice mass relative to pre-industrial times) even when temperatures were still rising. In MAGICC 4.1, this problem was avoided simply by keeping the GSIC melt term at its maximum value once the maximum was reached. The TAR formulation constrained this maximum to a melt of 18.72 cm relative to pre-industrial times – effectively fixing the total amount of GSIC ice mass at 18.72 cm sea-level equivalent.

A more realistic, physically based formulation has been given by Wigley and Raper (2005). This gives results that are consistent with the TAR out to 2100, but allows the total GSIC ice mass to be specified externally. This new formulation produces GSIC melt that rises asymptotically towards the total available amount of GSIC ice as warming continues – i.e., eventually, almost all of the GSIC ice melts if the world becomes warm enough. MAGICC 5.3 uses this new formulation. The default total GSIC ice mass (V_0) is set at 29 cm (it can be changed off line in the MAGICE.CFG configuration file). This is effectively the best-estimate value given in the IPCC Fourth Assessment Report (Meehl and Stocker, 2007). AR4 gives a best-estimate of 24 cm and scales up GSIC melt projections by 20% to account for outlet glaciers in Greenland and Antarctica. With the present GSIC model, the same effect can be achieved by scaling up V_0. For V_0 uncertainties we use the scaled-up AR4 uncertainty range, 18 to 44 cm. For timescales more than a few centuries, if warming were substantial, the Greenland/Antarctic "GSIC" contribution could be much higher than implied by the 20% V_0 scaling, as their total ice mass is well over 50 cm.

The other change made in MAGICC5.3 is to ignore the contributions from: (1) Greenland and Antartica due to the ongoing adjustment to past climatic change, (2) runoff from thawing of permafrost, and (3) deposition of sediment on the ocean floor. (Referred to as "non-melt" terms below.) These terms were assumed in the TAR to contribute to sea level rise at a constant rate, independent of the amount of future warming. It is now thought that these terms are small, smaller than was assumed in the TAR, so they were not considered in the AR4 (Jonathan Gregory, personal communication). For consistency they are ignored here.

No other changes have been made to the sea level modeling components. In the AR4 report (p. 845) it is stated that AR4 projections for the Antarctic sea level contribution "are similar to those of the TAR", while "Greenland … projections are larger by 0.01–0.04 m. (i.e., by 2100, these projections are 1 to 4 cm larger than the TAR projections). We have not adjusted the Greenland model to account for this.

MAGICC sea level projections are very similar to those in AR4, as the Table below shows.

***Table 3**: Sea level rise projections (cm) over 1990 to 2095 given by MAGICC – top numbers in each row. In column 4, the lower numbers in square brackets give the results published in the AR4. AR4 numbers (Meehl and Stocker, 2007, p. 820) are based on AOGCM results and are changes between 1980 to 1999 and 2090 to 2099.*

∆T2x	1.5	3.0	3.0	3.0	6.0
Ice melt	Low	Low	Mid	High	High
A1B	14	24	35 [35]	46	68
A1FI	19	32	45 [43]	59	86
A1T	13	21	33 [33]	44	65
A2	16	27	38 [37]	50	73
B1	10	17	26 [28]	35	52
B2	12	20	31 [31]	41	61

The MAGICC/AR4 similarity is partly fortuitous as MAGICC gives slightly higher expansion and slightly lower results for GSIC and Greenland contributions. The differences in these component sea level terms are, however, within their uncertainty ranges. Nevertheless, the positive bias in thermal expansion results from MAGICC compared with AOGCMs (noted in the AR4, p.844) is a concern that is currently under investigation. (AR4, p. 844, also claims that MAGICC has a slight warm bias in projections of global-mean temperature, but this is unfounded. The apparent bias is due partly to forcing differences between the standard MAGICC forcings and those used in AR4 AOGCMs, and to other factors that make a true like-with-like comparison difficult – see Meinshausen et al., 2008.)

The uncertainty bounds for sea level rise in Table 3 differ from those given in the AR4. This is because we concatenate uncertainty limits for all factors that contribute to sea level rise uncertainties. It is unlikely that all of these factors would act in the same direction (although some would because they are determined by the same underlying and more fundamental uncertainties, such as those in the climate sensitivity). Thus, within the limitations of the models used, the uncertainties given by MAGICC represent extreme, low probability values. AR4 uncertainty ranges can be simulated approximately from MAGICC results by halving the differences between the MAGICC extreme and best-estimate values. AR4 uncertainties (AR4, p. 820) are stated to be “5 to 95% intervals characterizing the spread of model results”. Given that the models used do not represent the full uncertainty range (they are often referred to as an “ensemble of opportunity”), it is likely that the 5 to 95% range given in the AR4 underestimates the “true” 5 to 95% range.

It should be noted that neither the AR4 nor the TAR projections (nor MAGICC) include the possible effects of accelerated ice flow in Greenland and/or Antarctica. In the AR4 this is judged to increase the upper bound for AR4 projections to 2100 by 9 to 17 cm (AR4, p. 821). The same increase should be considered applicable to the MAGICC projections.

Balancing the CH4 and N2O budgets

In the TAR (and in earlier IPCC reports), because of uncertainties in the present-day CH_4 and N_2O budgets, and because emissions data produced in most scenarios give only anthropogenic emissions, it was necessary to balance the gas budgets. This was done using a simple box-model relationship: $dC/dt = E/\beta + C/\tau$, where C is concentration, E is emissions, β is a units conversion factor, and τ is lifetime. If dC/dt, C and τ are known in some reference year, then E can be calculated. If the scenario value is E_0, then a correction factor $(E - E_0)$ can be calculated and this is applied to all future emissions. If E_0 is solely the anthropogenic emissions value, then the difference $E - E_0$ represents the present contribution from natural emissions sources. Applying this correction to all future emissions is based on the assumption that natural emissions will remain constant. For CH_4 at least, there is evidence that this has not be so in the past (Osborn and Wigley, 1994), and strong evidence that it will not be so in the future. Version 5.3 of MAGICC does not account for future natural emissions changes, although it is relatively easy to do this if one has an idea of the possible effects of global warming on natural emissions.

In MAGICC 5.3, a minor change has been made to the rate of change of methane concentration in the year 2000 that is used for balancing the initial methane budget. The small decrease, from 8.0 ppb/yr to 3.5 ppb/yr, is in better accord with observations. This reduces the calculated natural methane emissions level in 1990 (and subsequently) from 279.0 to 266.5 TgCH4/yr. Consequently, future CH_4 concentrations are reduced relative to those calculated by version 4.1. For example, 2100 concentrations for the A1B scenario drop from 1965 to 1908 ppb. The effect of this on future climate projections is negligible.

Changes to the climate sensitivity

The only other changes are to the estimates of climate sensitivity. In accord with AR4, the best-estimate of the climate sensitivity ($\Delta T2x$) is now 3.0°C – previously 2.6°C. The AR4 uncertainty range for sensitivity is 2.0–4.5°C, designated as the "likely" range (66% confidence interval). If the distribution is assumed to be log-normal, this corresponds to a 90% confidence interval of 1.49–6.04°C. In MAGICC 4.1, the 90% confidence interval and best estimate values were set at 1.5°C (low), 2.6°C (mid), and 4.5°C (high). These have been re-set to 1.5°C (low), 3.0°C (mid), and 6.0°C (high). The increase at the high end is substantial, and leads to noticeably higher "upper bound" projections of temperature and sea level. This increased probability of a high sensitivity value is in accord with the latest empirical estimates of the climate sensitivity. The AR4 reviews probabilistic sensitivity estimates from the recent literature in two places, in the Technical Summary (Solomon et al.,. 2007) and in the "detection and attribution" chapter (Hegerl and Zwiers, 2007). In the Technical Summary (p. 65), 95th percentile results from 12 studies range from 4.4°C to 9.2°C, while the probability of a sensitivity above 6.0°C ranges from near zero to 38%. In Hegerl and Zwiers (p. 672), 7 of these studies are summarized. The 95th percentile values here range from 4.4°C to 9.2°C. (The slightly different lower bound probably results from difficulties in extracting numerical values fro the graphical results that are shown.)

3.2 SCENGEN CHANGES

(1) **New AOGCMs**. The AOGCM data base used in version 4.1 (viz. CMIP2) has been replaced to make use of model results generated for the IPCC Fourth Assessment Report (AR4). The primary advantages here are that these are more up-to-date model results (state-of-the-art as of June 2007), and that these newer models have, in general, higher spatial resolution than the older models. With higher native spatial resolution in the newer AOGCMs it has been possible to re-grid all model results to 2.5 by 2.5 degrees, latitude/longitude without loss of information. Model results in SCENGEN 4.1 were at 5 by 5 degrees. For the AR4 models, most have resolution that is finer than 2.5 by 2.5.

These data sets are housed at the Program for Climate Model Development and Intercomparison (PCMDI) at the US DOE Lawrence Livermore National Laboratory (LLNL). This data set is now referred to as the CMIP3 data base. Details are available at:

http://www-pcmdi.llnl.gov/ipcc/model_documentation/ipcc_model_documentation.php

(See the folder C:\SG53\SCEN-53\SG-MANS\ModelDoc for documentation data.)

There are 24 models currently in the CMIP3 data base, but only 20 have the full set of data required for use in SCENGEN. The 20 models are listed in Table 4, which gives their CMIP3 designation and the 8 character label used by the SCENGEN software. The four models not used are listed at the bottom of the Table. Note that these four models have no SCENGEN label.

Some words of caution apply to some of the models. For the **FGOALSg-1.0** model, under "known biases and improvements", the model developers state: "The … model shows much more sea ice extension than the observation", and "… while our submitted model data are suitable for tropical and subtropical studies, we do not suggest to use these data in mid-latitudes". An improved version of this model has been developed, but it is not available in the CMIP3 data base.

Although the **GISS-ER** model is included in the SCENGEN data base, one should be cautious in using this model as its projections differ markedly from those of other models. Either the model is very strange, or there are some serious errors in the model data sets housed in the CMIP3 archive. A similar note of caution applies to NCAR's **PCM**. As with GISS-ER, PCM projections differ markedly from those of other models. Furthermore, PCM's validation performance (i.e., in simulations of present-day climate) is generally poor relative to other models. More information on these two models is given in Section 6 below.

Some caution should also be exercised with **MIROC3.2(hires)** because this model appears to have a very high climate sensitivity (estimated at 5.6^{o}C equilibrium warming for 2xCO_2). However, as SCENGEN uses normalized data files, thereby removing the direct influence of climate sensitivity, this may not be a serious issue. Apart from its high sensitivity, the model appears to be quite consistent with the other models that are in the SCENGEN 5.3 data base (see Section 6).

***Table 4**: AOGCMs used in SCENGEN 5.3.*

CMIP3 designator	Country	SCENGEN name
BCCR-BCM2.0	Norway	BCCRBCM2
CCSM3	USA	CCSM—30
CGCM3.1(T47)	Canada	CCCMA-31
CNRM-CM3	France	CNRM-CM3
CSIRO-Mk3.0	Australia	CSIRO-30
ECHAM5/MPI-OM	Germany	MPIECH-5
ECHO-G	Germany/Korea	ECHO---G
FGOALS-g1.0	China	FGOALS1G
GFDL-CM2.0	USA	GFDLCM20
GFDL-CM2.1	USA	GFDLCM21
GISS-EH	USA	GISS—EH
GISS-ER	USA	GISS—ER
INM-CM3.0	Russia	INMCM-30
IPSL-CM4	France	IPSL_CM4
MIROC3.2(hires)	Japan	MIROC-HI
MIROC3.2(medres)	Japan	MIROCMED
MRI-CGCM2.3.2	Japan	MRI-232A
PCM	USA	NCARPCM1
UKMO-HadCM3	UK	UKHADCM3
UKMO-HadGEM1	UK	UKHADGEM
BCC-CM1	China	
CGCM3.1(T63)	Canada	
GISS-AOM	USA	
INGV-SXG	Italy	

(2) **Improved spatial resolution**. All the new (CMIP3) AOGCM data have been re-gridded to a common 2.5^{o} by 2.5^{o} latitude/longitude grid (compared with 5^{o} by 5^{o} in version 4.1). For the CMIP3 models, most have resolution that is finer than 2.5 by 2.5. The exceptions are ECHO-G, GISS-EH, GISS-ER and INM-CM3.0.

(3) **Mean sea level pressure** (MSLP) has been added as an output variable. Note that there are no data for MSLP for the aerosol response patterns, so projected MSLP changes are simply the greenhouse-gas responses scaled up to the true global-mean temperature.

(4) **New observed data bases** (at 2.5 by 2.5 resolution) have been added, replacing the previous 5 by 5 resolution data sets. These data sets have a common 20-year reference period, 1980-99. Temperature data now come from the European Centre for Medium-range Weather Forecasting's (ECMWF) reanalysis data set, ERA40. ERA40 is a spatially complete data set. For the 20-year averaging period, ERA40 data are indistinguishable from other spatially complete temperature data sets. For precipitation data, we still use the CMAP data set. An earlier CMAP data set (at 5 by 5 resolution) was used in version 4.1. Version 5.3 uses the latest 2.5 by 2.5 degree resolution version of CMAP. For MSLP, ERA40 data are used.

(5) **Spatial smoothing**. An option is available now to use and display spatially smoothed data. The smoothing is done simply by area averaging of the nine 2.5 by 2.5 cells surrounding a given grid box. Visually, the effect of this smoothing on the displayed maps is minor. However, smoothed results for individual grid boxes can be significantly different from unsmoothed data. The value of smoothing is that it allows the user to obtain a 9-box average by selecting or clicking on a single grid box. For impacts work, use of 9-box averages produces less spatially noisy results then using single (unsmoothed) grid boxes. If the smoothing option is selected, all display files are smoothed. These are the files that are also given as latitude/longitude arrays in IMOUT or SDOUT (see below). For all other output files (such as AREAAVES.OUT), smoothing is ignored, and raw, unsmoothed data are always used for calculations.

(6) **New color palettes and contouring choices** are now available. For color palettes, the original rainbow version is available as default. In addition, one may now choose either a red-blue color palette, or a palette similar to one that has been employed by the IPCC AR4. For contouring, the default is as in version 4.1. In addition, one may now select a max-min contouring system where the lowest and highest contour values correspond as nearly as possible (given the constraint of having "sensible" contour values and intervals) to the 90% range of grid-box values. In other words, approximately 5% of the grid-box values will be represented by the top color in the palette and 5% of the grid-box values will be represented by the bottom color in the palette. As in version 4.1, each map display gives the highest and lowest grid-box values as numerical values ("Range" in version 4.1, now "Global range").

(7) Two **new output displays** may be selected using an overwrite facility for "Temporal SNR". The first is "S.D. change SNR" (SDSNR), which shows an inter-model Signal-to-Noise Ratio for changes in variability (where "variability" here is determined by the inter-annual standard deviation (s.d.) calculated over a 20-year period). SDSNR is defined as the model average of the normalized s.d. changes divided by the inter-model s.d. of these normalized s.d. changes. This is a time-independent quantity that shows the uncertainty in projections of s.d. relative to inter-model differences in these projections. SDSNR values are invariably small, showing that projections of variability changes are highly uncertain.

The second new display is for "S.D. base uncert." (SDUNCERT), which shows uncertainties in model baseline s.d. values as determined by inter-model differences in grid-box s.d. values. These are also expressed as a Signal-to-Noise Ratio, the model-mean baseline s.d. value divided by the inter-model standard deviation of the model baseline s.d.s.

(8) **New output files**. A number of new output data files are produced and given in …ENGINE/IMOUT and …ENGINE/SDOUT. The full set of output files is listed below in Table 5. These results in these output files are specific to the user selections of: scenario; MAGICC model (user or default); variable and season; analysis year (i.e., global-mean warming amount); and scaling method.

There are two types of output file, latitude/longitude arrays and tabulated results. The tabulated results files in folder IMOUT are AREAAVES.OUT, IMCORRS.OUT, IMFILES.OUT, OUTLIERS.OUT and VALIDN.OUT. The tabulated results files in folder SDOUT are FILES.OUT and SDCORRS.OUT. Note that spatial smoothing is never applied to these files – smoothing is only applied to the latitude/longitude array files. For the array files, full global arrays are always given even if the user has selected a smaller region. For the tabulated results files, the results always apply to the user-selected region.

Although the user must select a specific type of analysis, the software calculates results for all possible analyses, so the results in folders IMOUT and SDOUT are always complete.

***Table 5**: SCENGEN output files.* These files comprise three types of output: latitude/longitude arrays that are the numerical values for fields that are or can be displayed in SCENGEN ("displayable firkds"); supplementary latitude/longitude output fields that cannot be displayed; and tabulated results that may be used for diagnostic studies.

SG50/SCEN-50/ENGINE/IMOUT
(displayable fields, also given in …ENGINE/SCENGEN)*

ABSDEL.OUT	: Model mean of absolute changes
*ABS-MOD.OUT	: New mean state (with aerosols) using model-mean baseline
*ABS-OBS.OUT	: New mean state (with aerosols) using observed baseline
AEROSOL.OUT	: Scaled change field (aerosols only)
AREAAVES.OUT	: Area averages over specified area – (1) model-by-model results for normalized GHG changes; (2) model-by-model results for baseline; (3) various model-mean results and observed baseline; (4) model-by-model scaled results (including aerosols)
*DRIFT.OUT	: This file will normally be blank. By putting IDRIFT=1 in EXTRA.CFG, drift (Def. 2 minus Def. 1) results will appear here.
ERROR.OUT	: Error fields. Model minus Observed for temperature and MSLP. % error (100(M – O)/O)) for precipitation
GHANDAER.OUT	: Scaled changes, model mean (with aerosols): sum of AEROSOL.OUT and GHGDELTA.OUT
GHGDELTA.OUT	: Scaled changes, model mean (GHG only)
IMCORRS.OUT	: Inter-model correlation results for normalized changes in mean state calculated over the specified area.
IMFIELDS.OUT	: Summary of fields, GHANDAER, GHGDELTA, AEROSOL, INTER-SD, IM-SNR, PROBINCR, NUM-INCR, MODBASE, OBSBASE, ERROR, ABS-OBS, ABS-MOD
IMFILES.OUT	: List of data files opened and read by INTERNN2.FOR. Also displays the selected area as a latitude/longitude array of 1s and 0s.
*IM-SNR.OUT	: Inter-model Signal-to-Noise Ratio for changes in mean state – SNR = change in mean state divided by inter-model standard deviation (independent of time). Same as INTERSNR.OUT in SDOUT, but 3 decimals instead of 2.
INTER-SD.OUT	: Inter-model standard deviation for normalized GHG change fields
*MODBASE.OUT	: Model-mean baseline
NORMDEL.OUT	: Model-mean of normalized GHG change fields
NUM-INCR.OUT	: Number of models with GHG changes above zero
*OBSBASE.OUT	: Observed baseline
OUTLIERS.OUT	: Outlier analysis – comparing model-i normalized GHG changes with average of remaining models. Analysis performed over the specified area.
*PROBINCR.OUT	: Probability of a change above zero
RKERROR.OUT	: RK error field – RK error = SQRT((M – O)^2/(OSD)^2), M = model mean baseline, O = observed baseline, OSD = observed baseline standard deviation.
SDERROR.OUT	: Standard deviation error field – 100((MSD – OSD)/OSD), MSD = model-mean baseline standard deviation.
SDINDEX.OUT	: S.D. bias field – SDINDEX = SQRT(0.5(RRR + 1/RRR)) where RRR = ((observed s.d.)/(model-mean s.d.))^2.
SDMEAN.OUT	: Model-mean baseline standard deviation field (denoted MSD above).
SDOBS.OUT	: Observed baseline standard deviation field (denoted OSD above).
VALIDN.OUT	: Validation statistics, comparing model-i and model-mean baselines with observed baseline data. Uses pattern correlation, RMS difference, bias (M – O), bias-corrected RMS difference, and RK index averaged over specified region.

SG50/SCEN-50/ENGINE/SDOUT
(displayable fields, also given in …ENGINE/SCENGEN)*
*(** displayable fields, that are not given in …ENGINE/SCENGEN)*

ALLDELTA.OUT	: Model average of changes in mean state (including aerosols).
*BAROFSNR.OUT	: Model average of temporal SNRs – SNR = mean state change divided by baseline model standard deviation
*BASE-SD.OUT	: Model average of baseline s.d.s
*DELTA-SD.OUT	: Model average of percentage changes in s.d.
FILES.OUT	: List of data files opened and read by STANDNN2.FOR. Also displays the selected area as a latitude/longitude array of 1s and 0s.
INTERSNR.OUT	: Inter-model Signal-to-Noise Ratio for changes in mean state – SNR = change in mean state divided by inter-model standard deviation (independent of time). Same as IM-SNR.OUT in IMOUT, but 2 decimals instead of 3.
SDCORRS.OUT	: Inter-model pattern correlation results for normalized s.d. change fields and baseline s.d. fields.
SDFIELDS.OUT	: Summary of fields, GHGDELTA, BASE-SD, DELTA-SD, BAROFSNR, SNROFBAR, INTERSNR, SDSNR, SDUNCERT. Plus correlation matrix for pattern correlations between these fields.
**SDSNR.OUT	: Inter-model SNRs for s.d. changes – SNR = model average of normalized s.d. changes divided by inter-model s.d. of normalized s.d. changes.
**SDUNCERT.OUT	: Uncertainty index for model-mean baseline s.d. – model average of baseline s.d.s divided by inter-model s.d. of baseline s.d.s.
SNROFBAR.OUT	: Temporal SNR of model-mean changes – model average of mean state changes divided by model average of baseline s.d.s.

SG50/SCEN-50/ENGINE/SCENGEN
The fields that can be displayed are all in this folder, except for SDSNR.OUT and SDUNCERT.OUT which are in the …ENGINE/SDOUT folder. Copies of these fields are also output to the …ENGINE/IMOUT and …ENGINE/SDOUT folders (see above) where they are given latitude-longitude labels. Note that DEL2USE is given a different file name in …ENGINE/IMOUT (viz. GHANDAER).

ABS-MOD.OUT	
ABS-OBS.OUT	
BAROFSNR.OUT	
BASE-SD.OUT	
DEL2USE.OUT	: Same as …ENGINE/IMOUT/GHANDAER.OUT.
DELTA-SD.OUT	
DRIFT.OUT	
ERROR.OUT	
IM-SNR.OUT	
MODBASE.OUT	
OBSBASE.OUT	
PROBINCR.OUT	

(9) **Model selection tools**. For impacts work it is often preferable to use average results for a selection of models. A standard method for selecting models is on the basis of their ability to accurately represent current climate, either for a particular region and/or for the globe. The output file VALIDN.OUT (model validation) can be used here. Two new validation statistics have been added. Another model selection criterion is to eliminate models whose projections are inconsistent with those of other models (i.e., one could decide to eliminate "outlier" models). The new output file "OUTLIERS.OUT" can be used here.

In version 4.1, VALIDN.OUT gave results for the pattern correlation between observed and modeled present-day climate, the root mean square (RMS) model/observed difference, and the model/observed bias (i.e., model area average minus observed area average). For "present-day" climate, version 4.1 used data from model control runs. Control run data are still used as the default, but it is now possible to use 1980-99 data from a 20th century climate simulation with the chosen model. To do this, the EXTRA.CFG file in folder ENGINE must be edited: NBASE must be changed to 4 from its default value of 3.

In neither case would one expect, even for a perfect model, perfect model/observed agreement. This is partly because neither the control nor the 20th century simulations uses forcings that are the same as those in the real world; and partly because, even with 20-year averages, the model and real worlds will have different manifestations of internally generated variability. Validation statistics differ by only small amounts for validation using control or 20th century data.

The new validation statistics are a bias-corrected RMS difference, and a validation statistic employed by Reichler and Kim (2008) ("RKERROR"). If two data sets have very different spatial means, then this can lead to inflated RMS differences. The bias-corrected RMS difference removes the spatial-mean difference before calculating the RMS difference. The RKERROR term is defined as the square root of a normalized mean-square model/observed difference (M – O), where the normalization is achieved by dividing each grid-box value of $(M - O)^2$ by the observed grid-box inter-annual variance. (There is an option to use the variance from the chosen model for normalization, accessible via an off-line CFG file edit.)

One should not place too much weight on RKERROR, as this can be very dependent on the normalizing term. Small local variances can lead to large grid-box RKERROR values that can have an unduly large influence on area averages. Insights into this problem can be gained by examining the RKERROR.OUT file in …ENGINE/IMOUT.

OUTLIERS.OUT uses a number of comparison statistics to define outliers. The comparisons are made between results for a chosen model and those for the average of all other selected models. The comparison statistics are as used in VALIDN.OUT (except that RKERROR is not used), viz. the pattern correlation, RMS difference, bias, and bias-corrected RMS difference.

(10) **Analysis of variability**. Variability in SCENGEN is characterized by the inter-annual standard deviation (s.d.) calculated over a 20-year reference period. Observed and model s.d. data come from the same sources as the mean state data. In version 4.1 it was possible only to examine model average fields for baseline s.d. and s.d. changes. The latter are derived only from CO_2-based patterns of s.d. change (as there are no s.d. data available for the aerosol fields). Scaling uses the full global warming projection, so the code effectively assumes that the patterns of s.d. change for CO2 forcing and aerosol forcing are similar.

Although these are still the primary s.d. display fields, it is now possible to display two fields that give an idea of the uncertainties in these displayed fields based on inter-model differences. These are: the inter-model Signal-to-Noise Ratio for s.d. changes (i.e., SDSNR = model average of normalized s.d. changes divided by the inter-model s.d. of these s.d. changes); and an uncertainty index for the model-mean baseline s.d. field (SDUNCERT = model average of baseline s.d. fields divided by the inter-model s.d. of these baseline s.d.s).

In addition, a number of new output files give information about: similarities between model s.d. change fields and similarities between model s.d. baseline fields; observed versus model s.d. differences (in percentage terms); an s.d. bias field based on work by Gleckler et al. (2008); and observed s.d. data (note that only model baseline s.d. data were available in version 4.1). These new output files are …

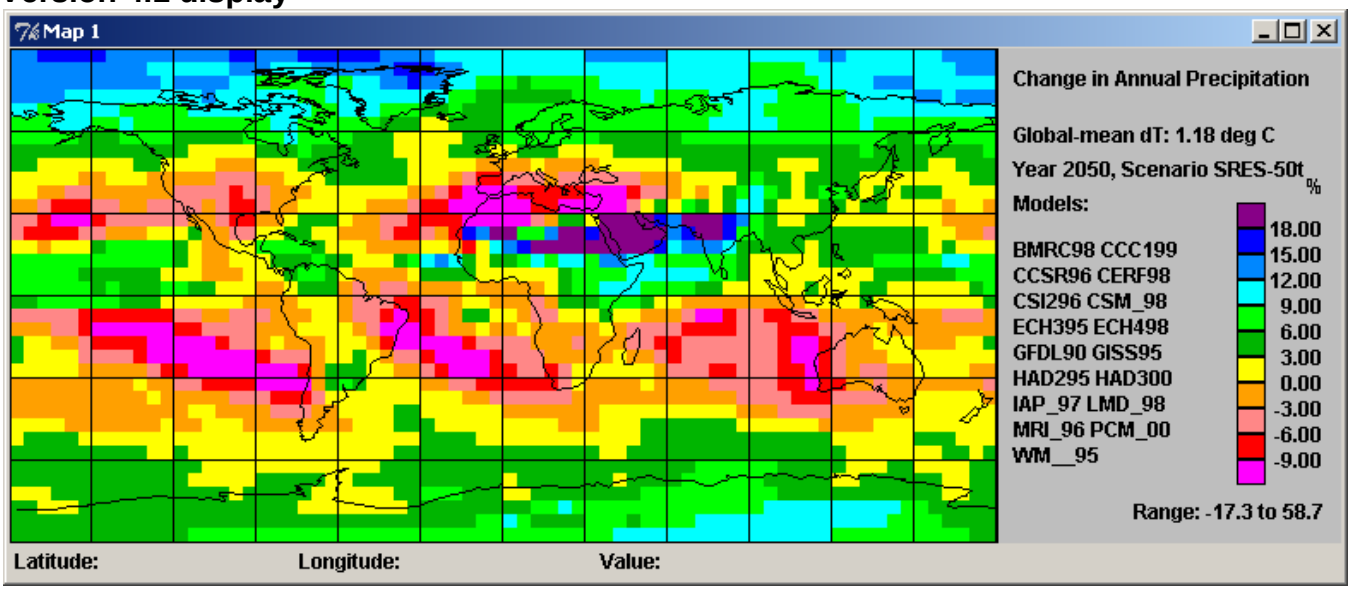
SDCORRS.OUT : Inter-model pattern correlation results for normalized s.d. change fields and baseline s.d. fields.
SDERROR.OUT : Standard deviation error field – 100((MSD – OSD)/OSD), MSD = model-mean baseline standard deviation.
SDINDEX.OUT : S.D. bias field – SDINDEX = SQRT(0.5(RRR + 1/RRR)) where RRR = ((observed s.d.)/(model-mean s.d.))^2.
SDOBS.OUT : Observed baseline standard deviation field (denoted OSD above).

SDINDEX is useful when considering area averages. With “raw” s.d. error data, positive errors and negative errors could cancel out giving a false impression of model skill. SDINDEX avoids this problem, but is still imperfect as it gives very small values (<1.0005, which rounds to 1.000 in the output) even when the absolute error is as large as 5%.

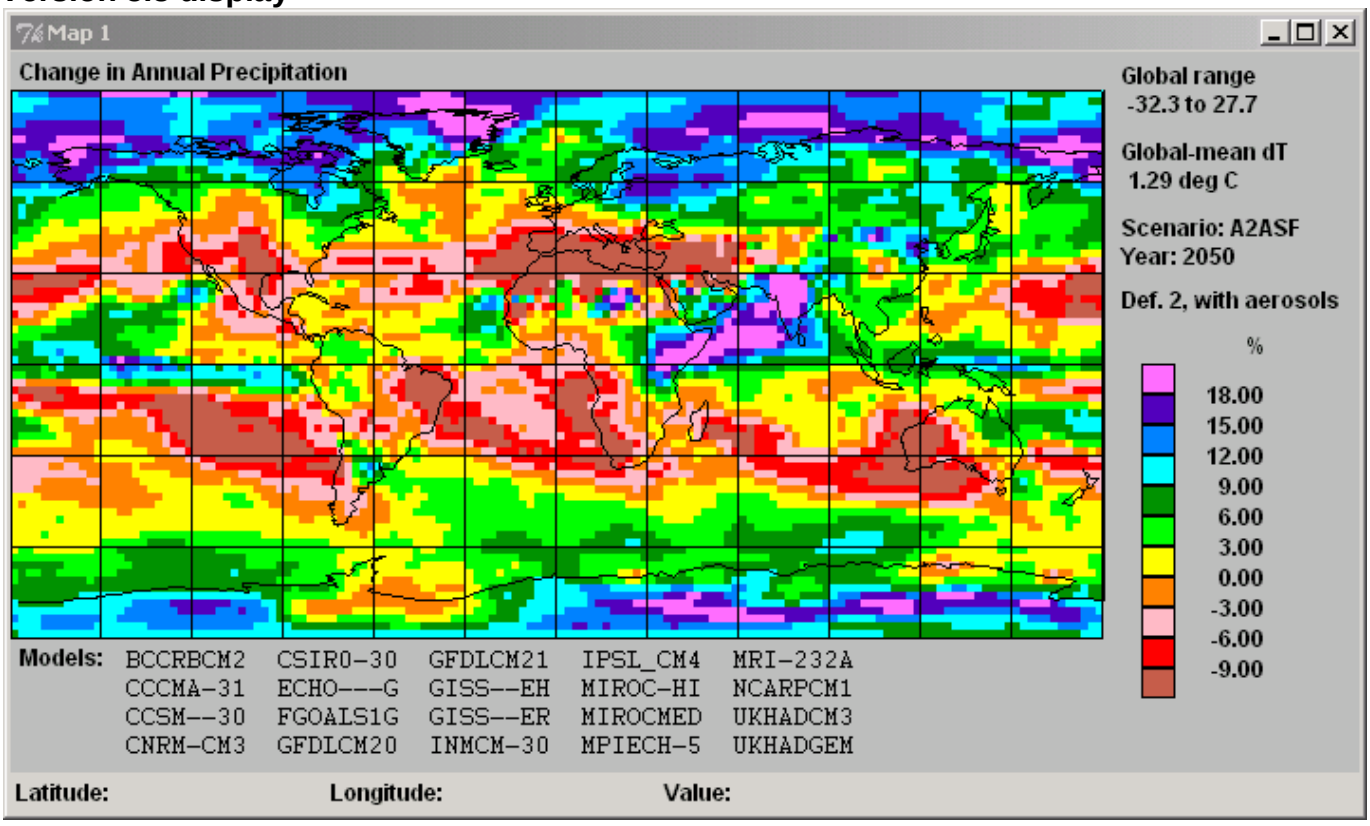
(11) A final **new output field (ABSDEL.OUT)** gives absolute changes in the mean state. This is only new for precipitation where, previously, only percentage change data were given.

(12) **Map displays in SCENGEN have been modified** to make the information displayed more clear. Examples showing the old (version 4.1) display followed by the new display are given below …

Version 4.1 display



Version 5.3 display

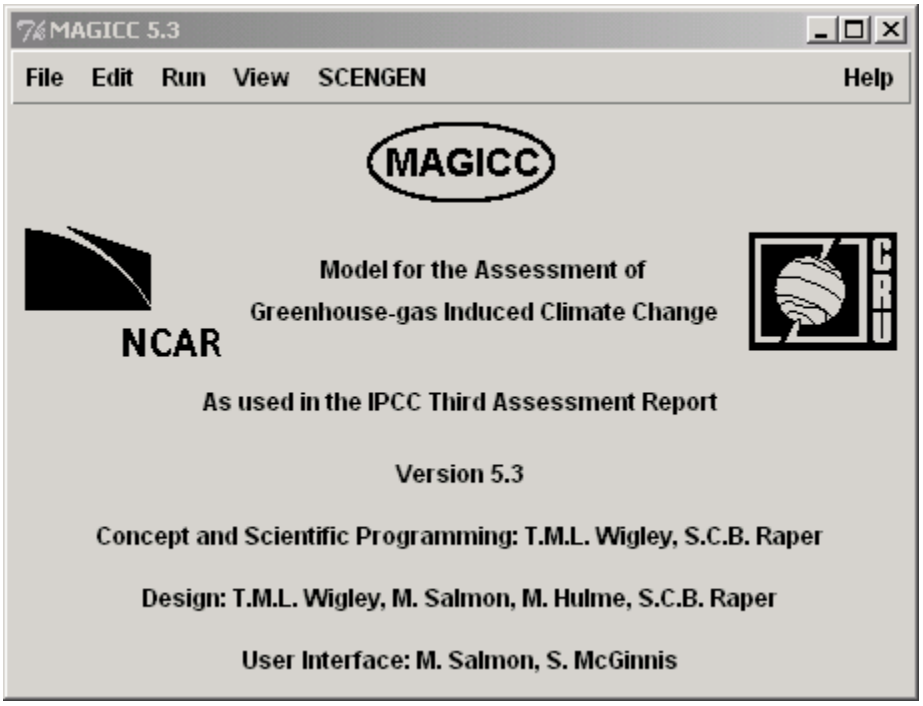


4. Running MAGICC:

In Windows, from drive “C” (Local disk), click successively on “SG53”, “SCEN-53”, and “MAGICC” to enter the operating directory. Then click on the MAGICC application (EXE) file. This will bring up the primary MAGICC/SCENGEN window – below.

The MAGICC directory contains all the emissions files (***.GAS), various configuration files that set model parameters (***.CFG), and a range of output files generated by MAGICC.

The SCEN-53 directory also contains sub-directories “RETO” (which contains all the AOGCM data), “NEWOBS” (which contains the new observed data), “SCENGEN” (which contains some of the gui code) and “ENGINE”. ENGINE in turn contains sub-directories “IMOUT” and “SGOUT” which give all the output files (see Table 5 above).



The first step in using MAGICC/SCENGEN is to click on “Edit”. This will display a pull-down menu with the choices “Emissions Scenarios”, “Model Parameters” and “Output Years”.

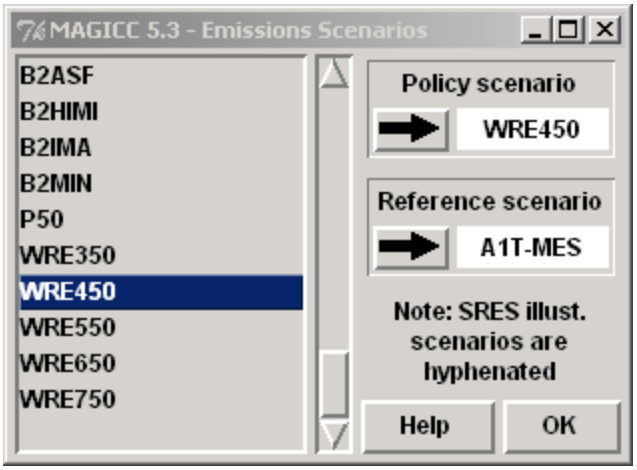
Under “Emissions Scenarios”, the user can select a Reference and Policy scenario. In the example below we use A1T-MES as the Reference scenario, and WRE450 as the Policy scenario. A1T-MES is one of the six illustrative scenarios from the SRES (Special Report on Emissions Scenarios; Nakićenović and Swart, 2000) set. WRE450 uses CO_2 emissions that

lead to CO_2 concentration stabilization at 450 ppm along the WRE (Wigley et al., 1996) pathway, with compatible non-CO_2 gas emissions that follow the extended MiniCAM Level 2 stabilization scenario (Wigley et al., 2008; Clarke et al., 2008 – see Appendix for further details). Emissions for WRE450 are defined out to 2400. Emissions for A1T-MES are defined only to 2100. The default setting for MAGICC is to run to 2100. A later run date can be selected by clicking on "Output Years" and re-setting the end date – see below.

Under "Model Parameters", most of the selections are self-explanatory. Examples will be given below. New features (in 4.1 and subsequently) are climate feedbacks on the carbon cycle, and (accessed by clicking on the default "User" model) the option to emulate a range of AOGCMs, specifically those used in Chapter 9 of the IPCC Third Assessment Report (TAR – Working Group I). AR4 AOGCMs will be added at a later date. The range of options under "Model Parameters" allows the user to carry out a variety of sensitivity studies. Examples will be given below.

Clicking on "Output Years" will bring up the "Output parameters" window (see below). Here, the user can control the years covered by the displays, and the years covered and time-step interval for output to the Reports files. Buttons on the right of the Output parameters window can be used to return to the default settings. The Output Years selection controls what data are available to SCENGEN. Most emissions scenarios in the library run only to 2100, so selecting a higher number for the last year in these cases will have no effect. The CO_2 stabilization scenarios, however, run to 2400. To obtain output over the full period it is necessary to select 2400 as the last year. Once done, this will allow SCENGEN results for these scenarios to be produced out to 2400.

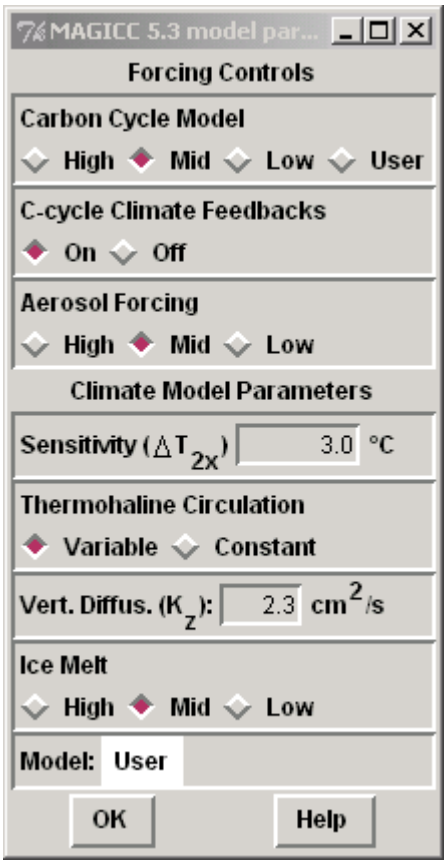
For a specific example, as noted above, we use A1T-MES for the Reference case and WRE450 for the Policy case. To select these, click on the Edit window and then Emissions Scenarios, scroll down to and select the chosen scenario(s), and then click on the appropriate selection arrow – as shown below.



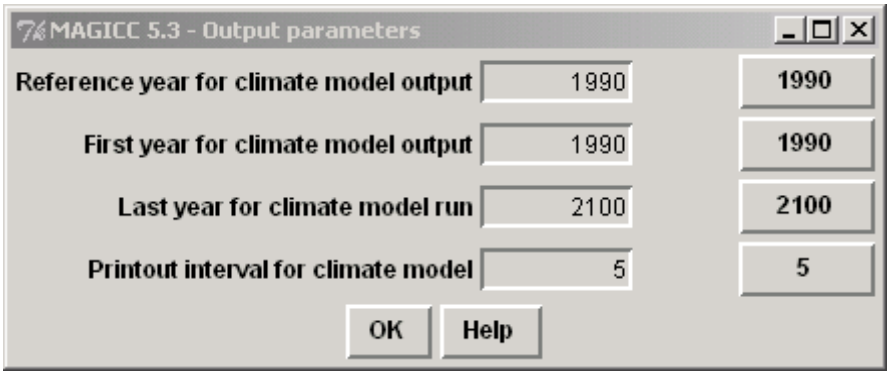
Click on "OK" to preserve the selected scenarios. This will close the "Emissions Scenarios" window.

An important thing to note with the emissions (*.GAS) files, should users wish to add their own files, is that there must be values given for the year 2000. This is because budget balancing for CH_4 and N_2O uses year-2000 data from the input emissions file. MAGICC will still run if there are no year-2000 data, but the CH_4 and N_2O results will be incorrect.

In the examples below we also consider the effects of a relatively high climate sensitivity, an equilibrium CO_2-doubling temperature change (ΔT2x) of 4.5°C. For now, however, we stick with the default model-parameter settings. The Model Parameters window opens up as below. Note that a sensitivity of 3.0°C, the default value, is shown in the Sensitivity box. We make no changes. Click on OK to close the window.



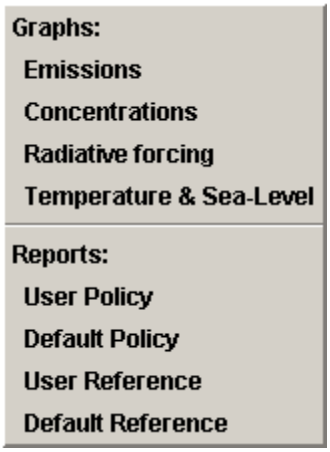
The next editing option is Output Years. Clicking on this will bring up the following window …



The default Last year is, as shown here, 2100. In this case the reference scenario (A1T-MES) is defined only out to 2100, while the Policy scenario (WRE450) is defined out to 2400. One could edit “Last year” to 2400 to show the full extent of the WRE450 results – but for now we will keep the default Last year. So simply click on OK with no changes.

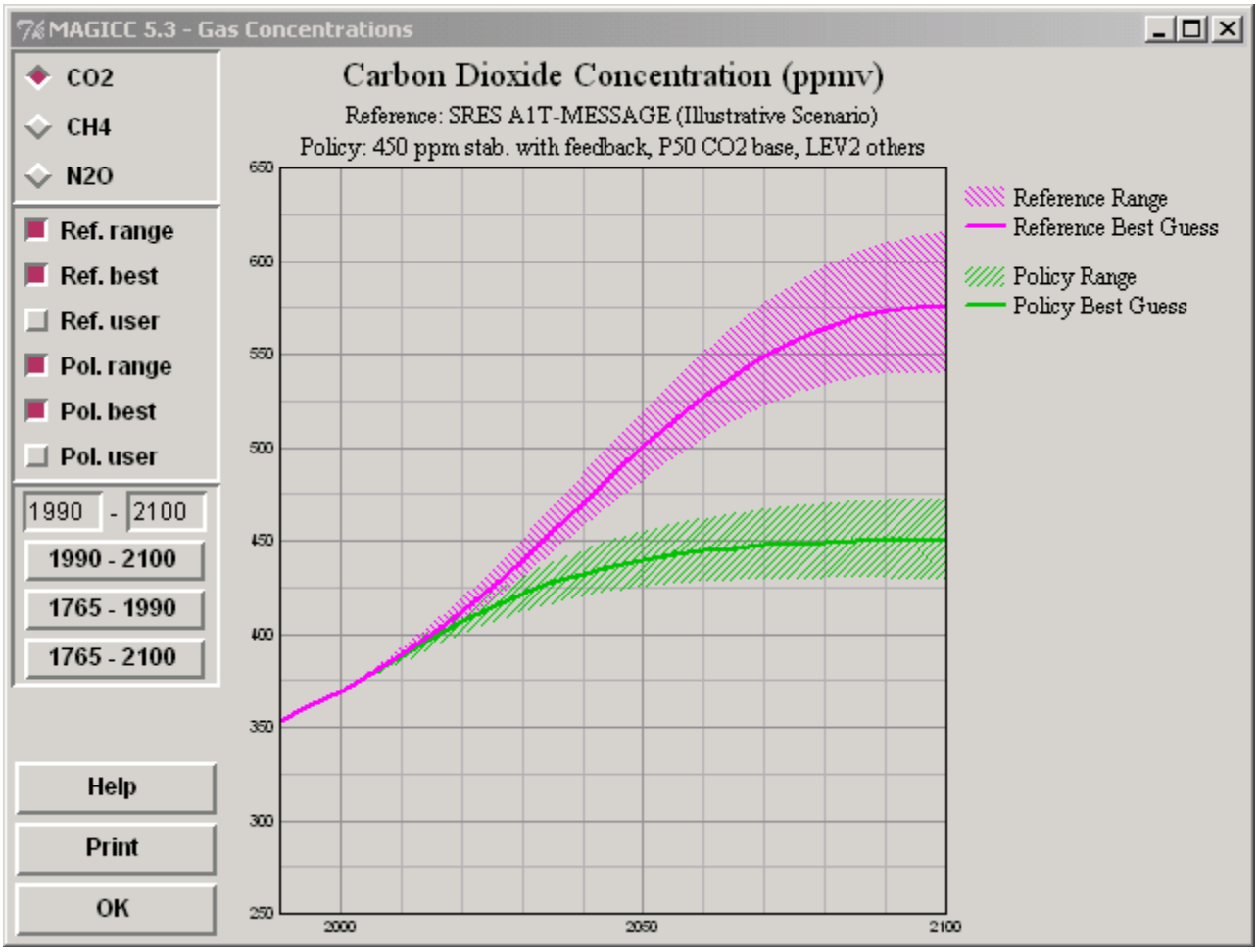
Unless further editing of the inputs is required, click on Run at the top of the main window. After a short time, the climate model will be run. Input emissions for the major gases and results for concentration changes, radiative forcing (by gas and total), global-mean temperature and global-mean sea level change can now be viewed by clicking on “View”.

If View is selected, the following window appears …..



The user can select either to view graphical output, or, in the **Reports** files, to access much more detailed tabulated output . Each Report file has results for sensitivities of $\Delta T2x$ = 1.5, 3.0, 6.0^{o}C and the user-selected sensitivity. Sea level output combines low sensitivity with low ice melt, and high sensitivity with high ice melt. Examples of the graphical output are shown below.

In some cases, numerical values will be given in the text. These have been extracted directly from the Reports files. We show results for concentration and global-mean temperature below. First, concentration …..



Currently, only results for CO_2, CH_4 and N_2O can be displayed. The default is CO_2. The selected display shows CO_2 concentrations for the default carbon cycle model, for both scenarios, together with an uncertainty range that is controlled solely by uncertainties in ocean uptake and CO_2 fertilization. The central, or "best" results include the effects of climate feedbacks on the carbon cycle, but the uncertainty ranges do not account for parameter uncertainties in the way climate feedbacks on the carbon cycle are modeled, nor for uncertainties associated with the effects of climate sensitivity uncertainties on the magnitude of these climate feedbacks.

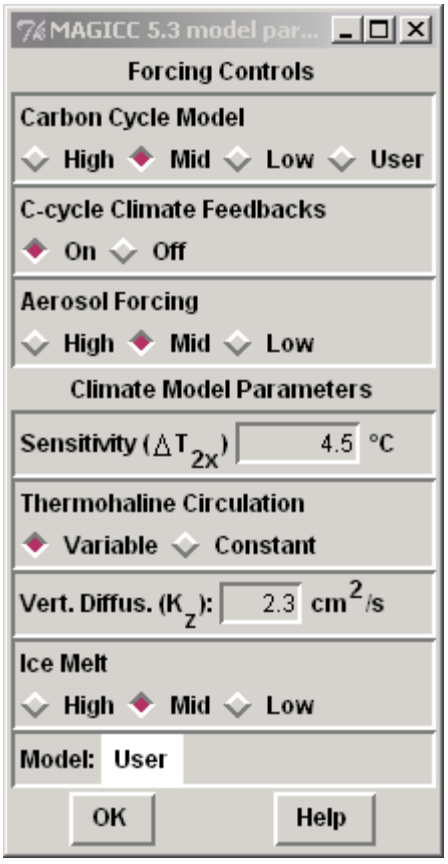
Note that uncertainty ranges displayed in MAGICC are always those for the User model. In this case, the User and Default models are the same.

To print out graphical results from MAGICC, use the Print button (this may not work with all printers). An alternative is to use the Alt-Prnt Scrn facility to save the active window, and then copy the window to a Word file, or to use specialist software like "SnagIt" – see below. A few of

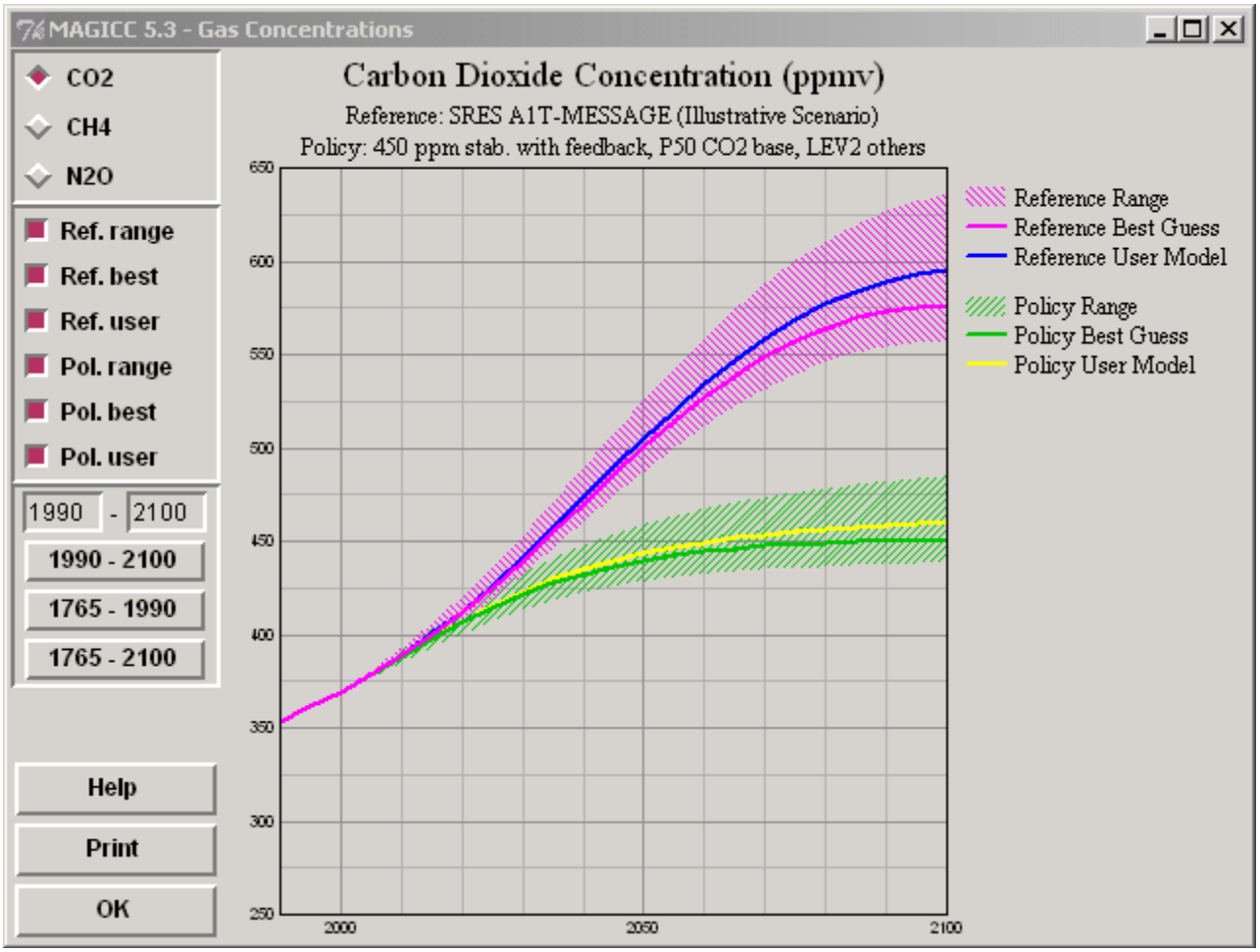
the graphical results in this document were produced using Alt-Prnt Scrn. Most results were produced using the commercial software “SnagIt” (http://www.techsmith.com/), which is highly recommended.

A key component of CO_2 projections is the feedback on the carbon cycle due to global warming. This is really a complex set of different feedbacks operating on a regional scale, some positive and some negative. On balance, however, these climate feedbacks are positive leading to significantly higher concentrations than would be the case if they were absent. We can illustrate the importance of these feedbacks with some specific permutations of the present example.

First, we increase the amount of warming simply by increasing the climate sensitivity. We do this by going back to the Edit button and editing Model Parameters. On the Model Parameters window we change Sensitivity to 4.5^{o}C – as below.



We select this with the OK button, and then click on Run. Then, through “View” we examine the CO_2 concentrations, as shown below …..

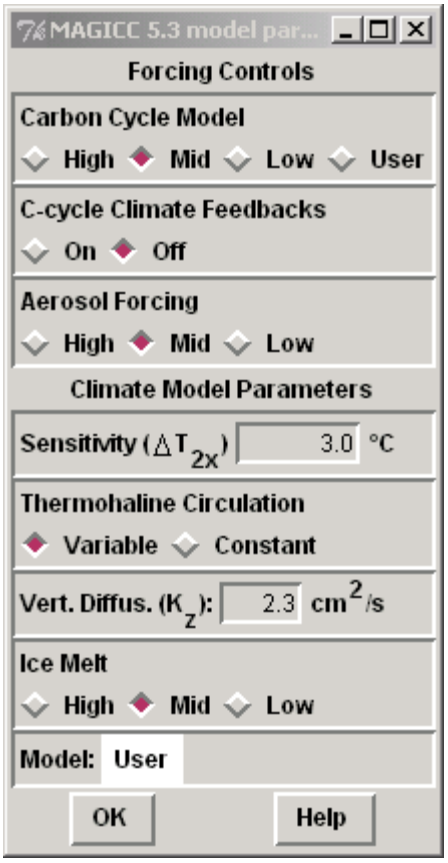


Effect of climate sensitivity on CO_2 concentration due to larger climate feedbacks that occur with the larger warming that results from choosing a larger climate sensivity: ΔT2x = 4.5°C (User Model) vs 3.0°C (Best Guess).

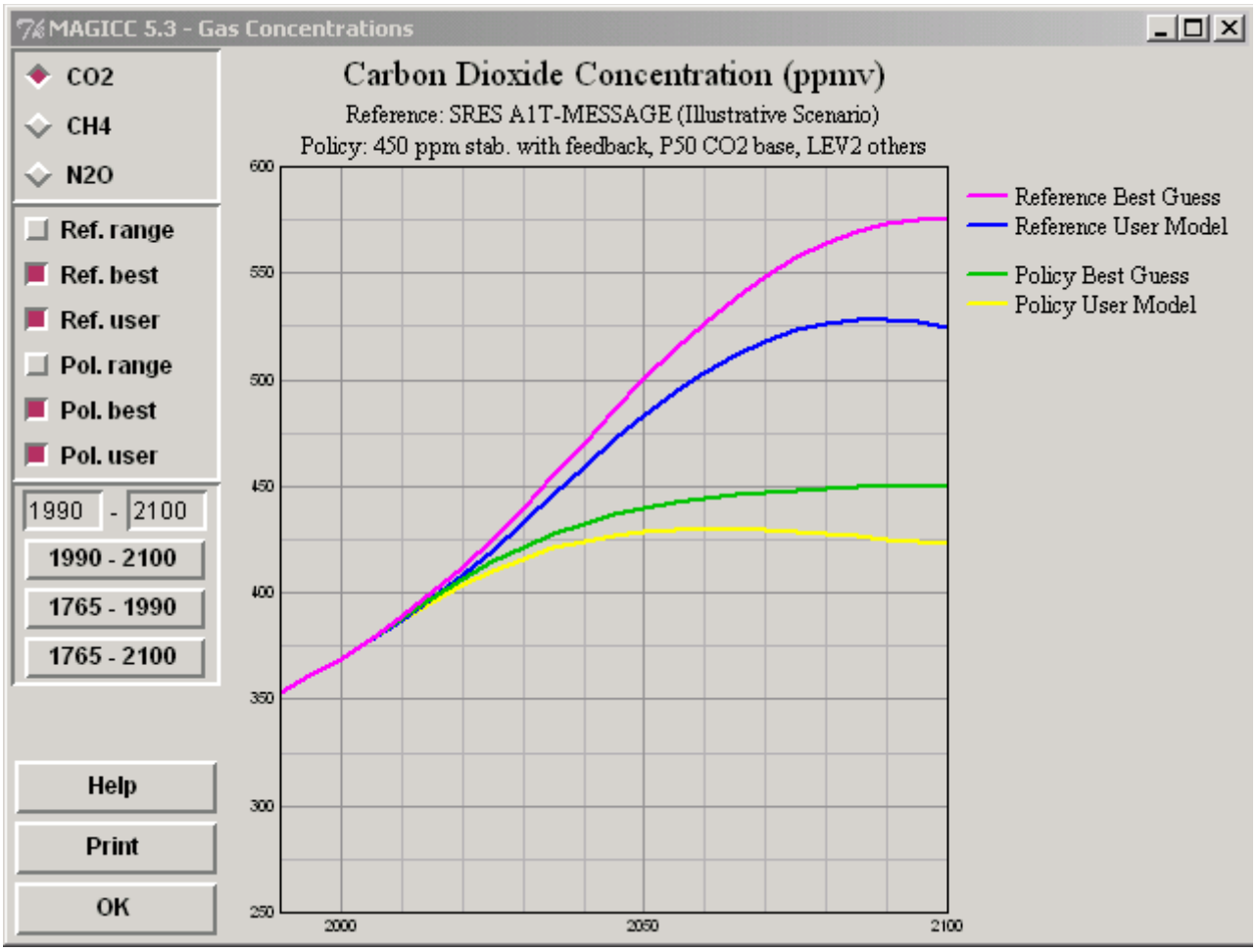
The display shows noticeably higher concentrations for the User Model (ΔT2x = 4.5) than for the Default Model (labeled “Best Guess” in the display), for both emissions scenarios. Note that the uncertainty bands are for the User Model.

The additional warming that occurs when a higher sensitivity is selected leads to a larger climate feedback on the carbon cycle, and, hence, larger concentrations. For the Reference (A1T) emissions scenario, warming in 2100 is 2.48°C for the default climate sensitivity (3.0°C) and 3.37°C for the user sensitivity (4.5°C). The corresponding 2100 CO_2 concentrations are 576 ppm and 595 ppm – an increase of 19 ppm for a warming increase of 0.9°C.

To further investigate climate feedbacks on the carbon cycle, we can choose to turn these feedbacks off. To do this we go back to the “Edit” button on the main window, and select “Off” in the C-cycle Climate Feedbacks panel – see below. Note that the user-selected climate sensitivity is still set at 4.5°C. For illustrating only the effects of climate feedbacks on the carbon cycle (i.e., on future CO_2 concentrations) we do not need to change this. This is because the no-feedback concentrations are, necessarily, independent of the sensitivity. However, if we want to examine the effects of these carbon cycle feedbacks alone on temperature, for example, we need to re-set the user climate sensitivity back to the default value of 3.0°C – as below.



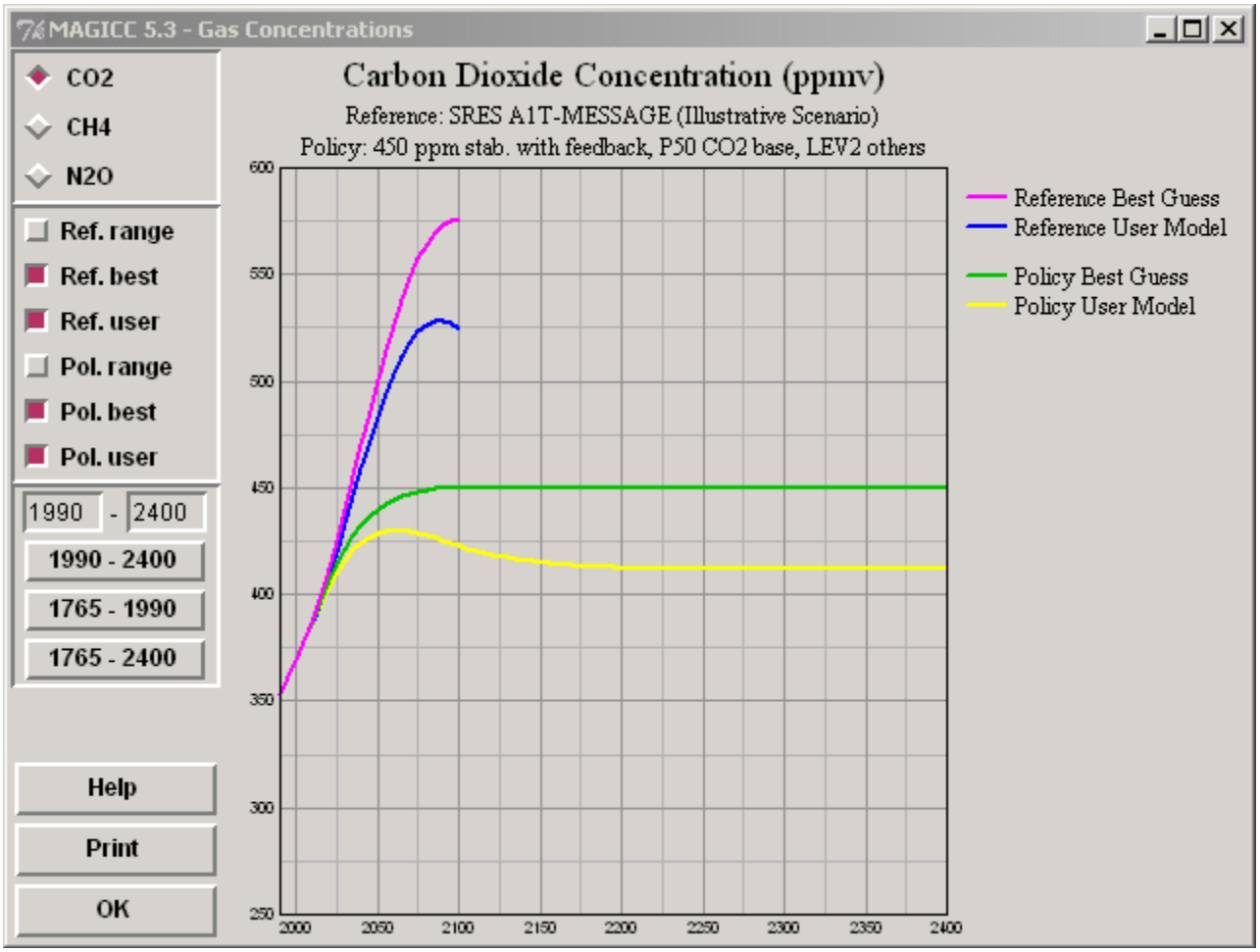
The User Model now is the same as the Default Model except that climate feedbacks on the carbon cycle have been turned off. Clicking on Run again, and then on View and Concentrations will bring up the display below.



Magnitude of climate feedbacks on the carbon cycle for a climate sensitivity of $\Delta T2x = 3.0^{o}C$. User Model shows the no-feedback case while Best Guess shows the default case which includes climate feedbacks.

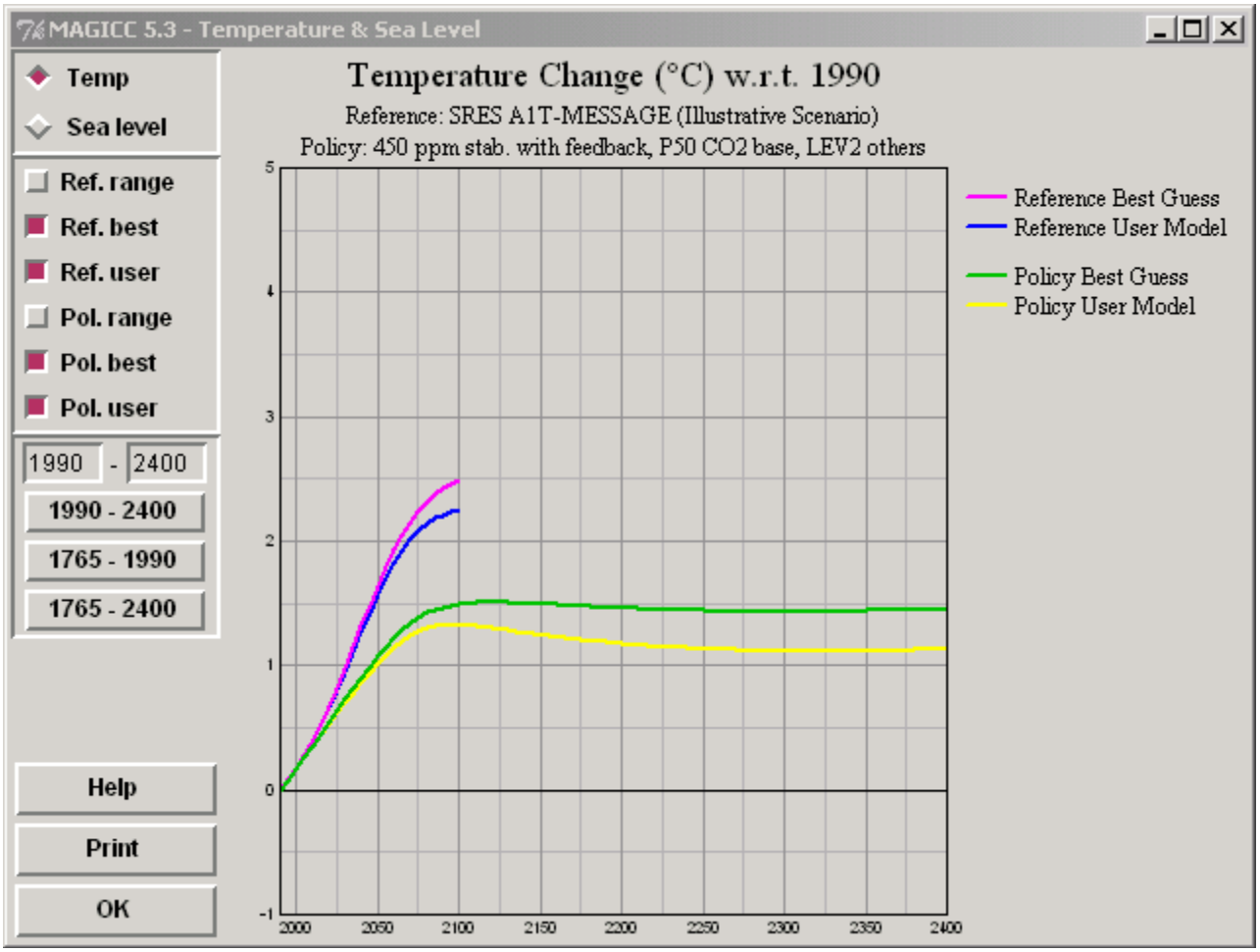
In this case, climate feedbacks on the carbon cycle are more noticeable, leading to significantly greater concentrations than would otherwise be obtained. The 2100 concentration with feedbacks is 576 ppm (as above). Without feedbacks the concentration is 525 ppm, so the feedbacks add 51 ppm to the 2100 concentration. A small part of this arises because the magnitude of the feedback depends on the temperature change, which is greater in the with-feedback case, 2.48^{o}C in 2100 compared with 2.24^{o}C.

For the Policy scenario, WRE450, concentrations are lower and the effect of climate feedbacks is to increase the 2100 concentration from 423 ppm to 450 ppm (+27 ppm). If we had run the analysis out to 2400 (by selecting 2400 in “Output Years” at the start), it could be seen that the difference increases over time, reaching 38 ppm by 2400 (see Figure below).

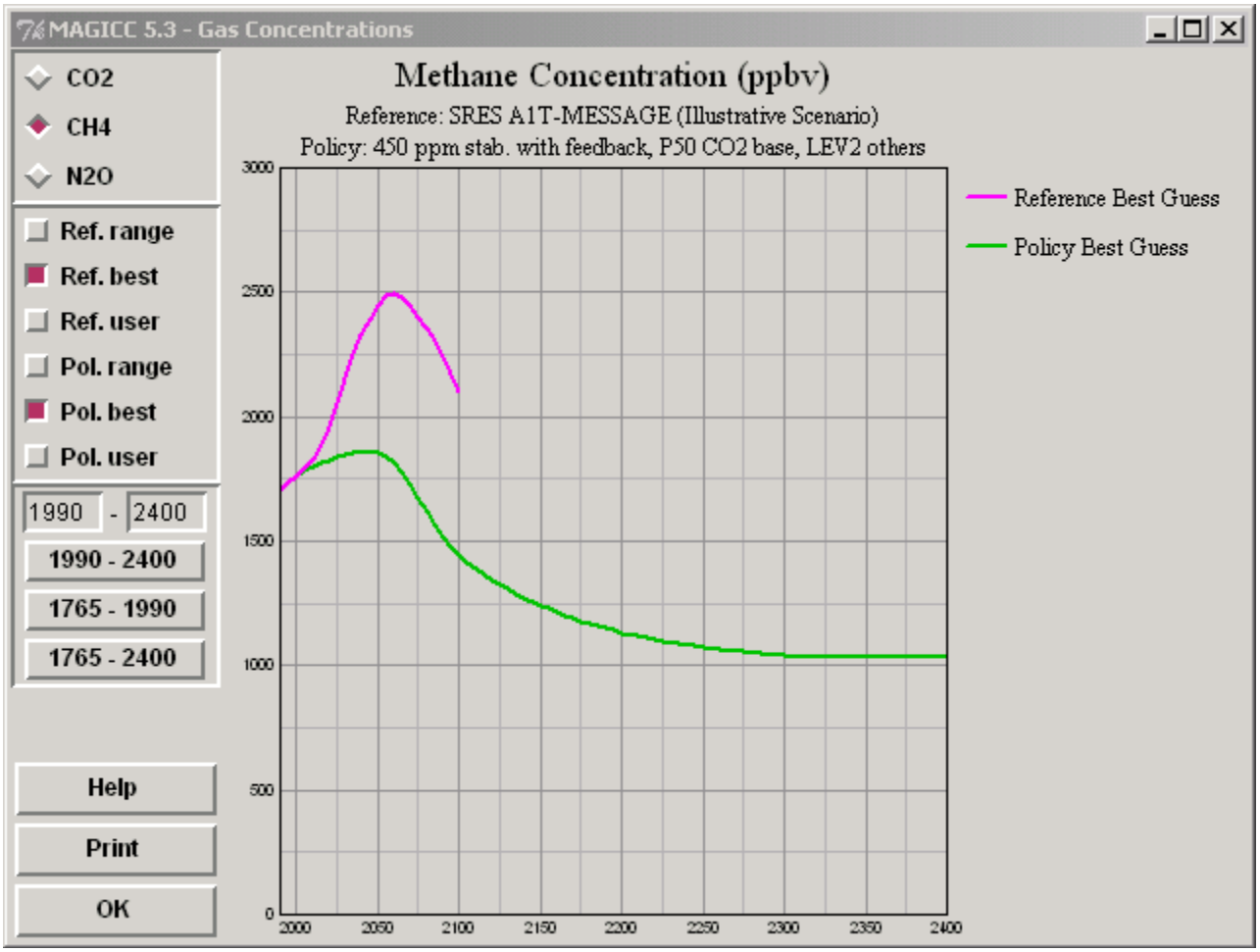


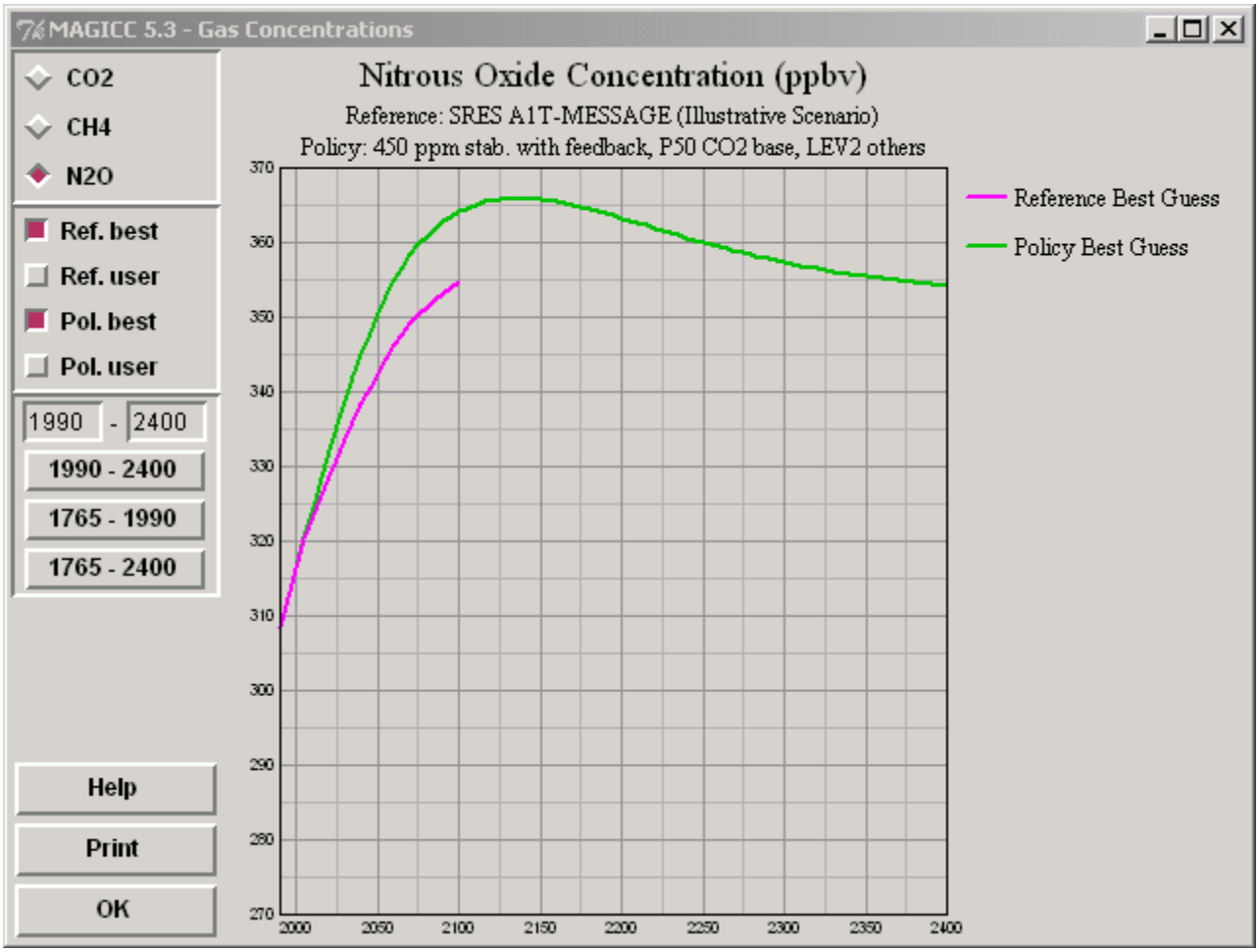
For global-mean temperature we show results for the same case, i.e., where the only user choice is to turn off climate feedbacks on the carbon cycle. From the concentration results above we expect the “User” cases to have slightly less warming than the default (“Best”) cases because of the lower CO_2 concentrations in the carbon-cycle, no-feedback case – as already noted.

The results for global-mean temperature change out to 2400 are shown below …



The difference between the “Best” (with feedbacks) and the “User” (no feedbacks) results tells us the magnitude of the effect of climate-related carbon cycle feedbacks on global-mean temperature. As expected from the concentration results, the effect of climate feedbacks is relatively small but significant. In 2100 the additional warming is about 0.25^{o}C for the Reference emissions scenario and 0.17^{o}C for the Policy scenario. By 2400 in the Policy scenario the difference rises to 0.33^{o}C. (These are results for the default climate sensitivity case.) Note that temperature stabilizes in the WRE450 case. This is in part because the WRE stabilization scenarios are now multi-gas stabilization scenarios in which all concentrations stabilize. Results for CH_4 and N_2O are shown below.

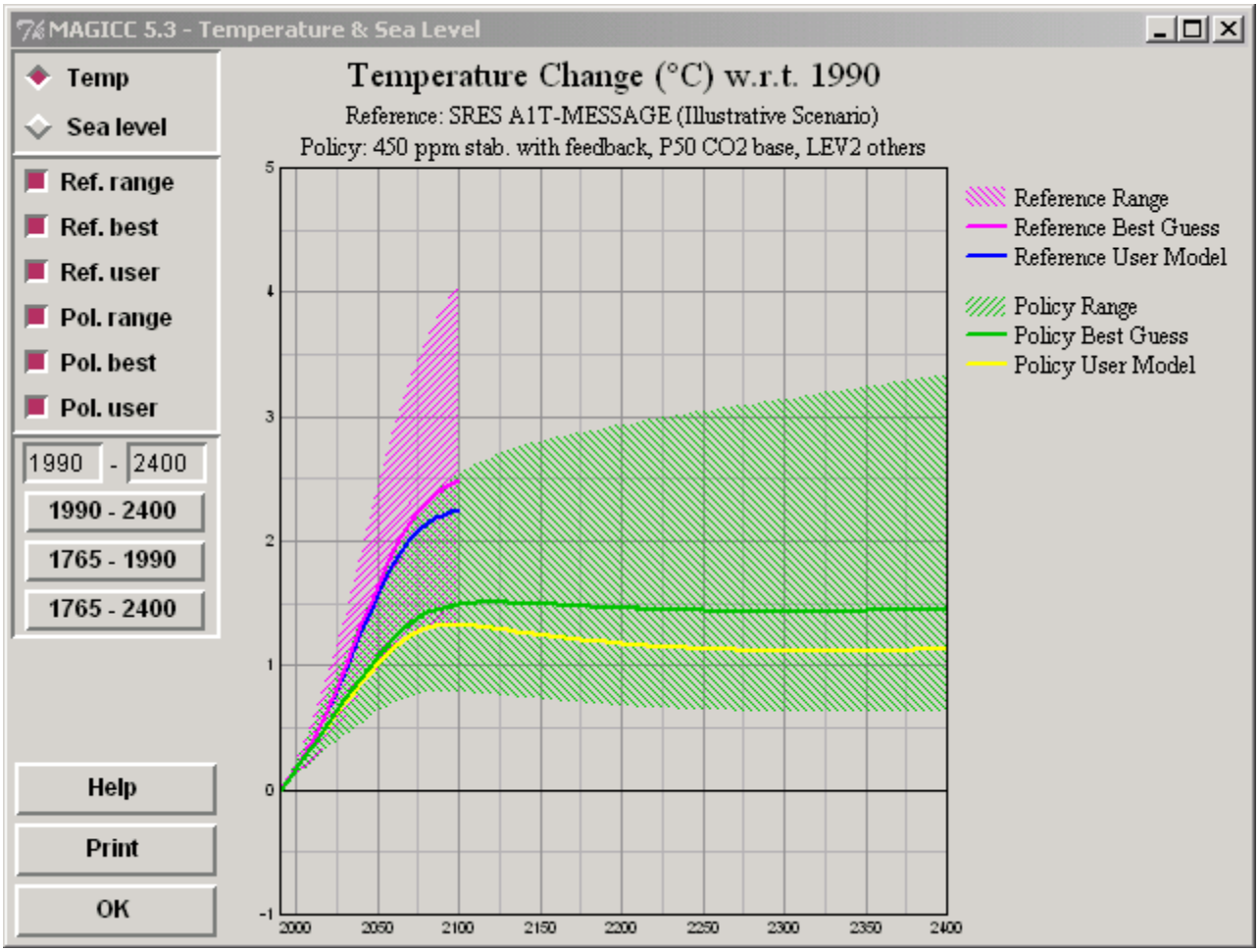

MAGICC 5.3 - Gas Concentrations
CO2
CH4
N2O
Ref. range
Ref. best
Ref. user
Pol. range
Pol. best
Pol. user
1990 - 2400
1990 - 2400
1765 - 1990
1765 - 2400
Help
Print
OK
Methane Concentration (ppbv)
Reference: SRES A1T-MESSAGE (Illustrative Scenario)
Policy: 450 ppm stab. with feedback, P50 CO2 base, LEV2 others
3000
2500
2000
1500
1000
500
0
2000
2050
2100
2150
2200
2250
2300
2350
2400
Reference Best Guess
Policy Best Guess



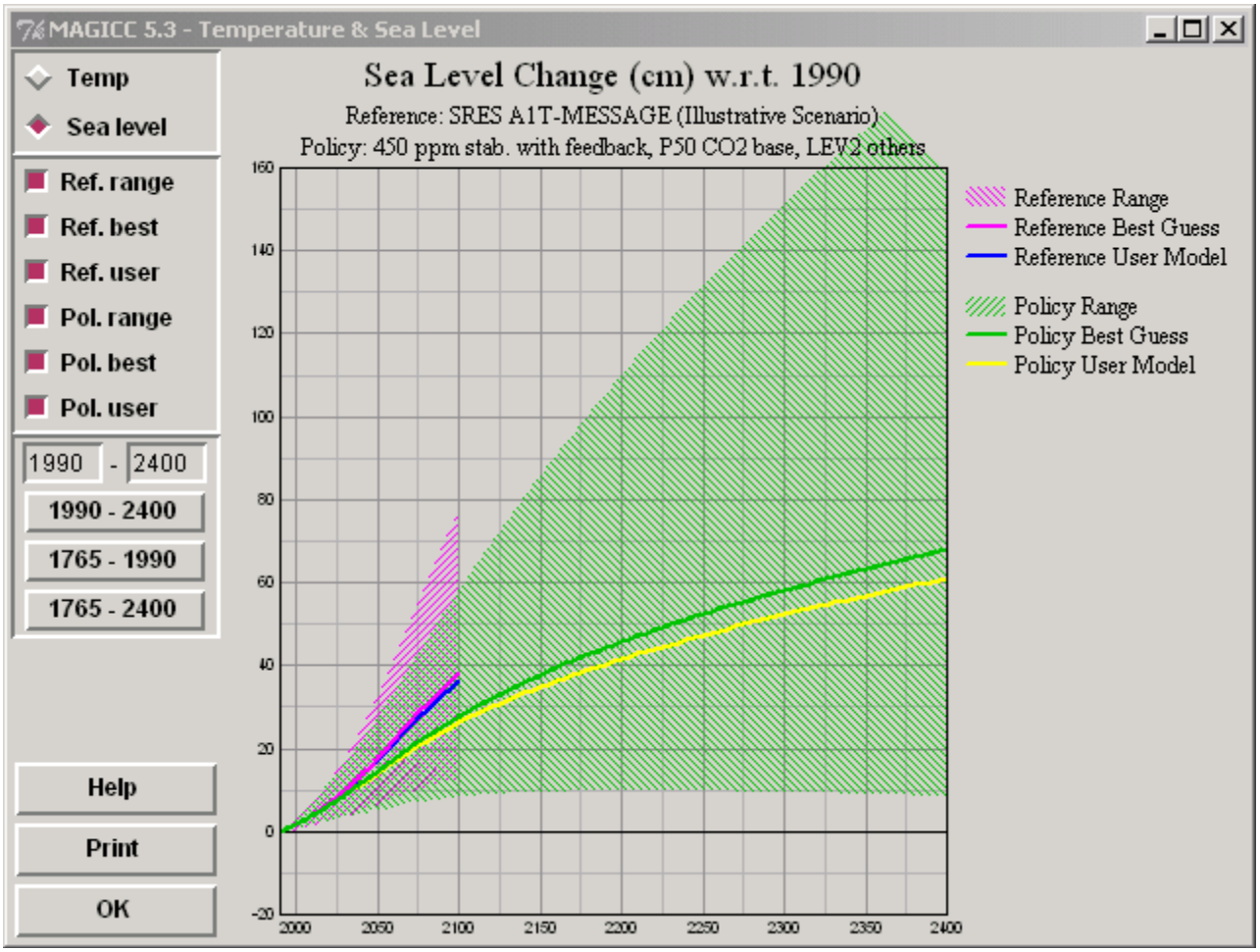
Interestingly, the no-climate-policy emissions and concentrations for N_2O in the A1T scenario are actually less than in the policy-driven WRE450 emissions scenario, where N_2O emissions come from the extended MiniCAM Level 2 multi-gas stabilization scenario. This illustrates the profound uncertainties in projecting N_2O emissions both in the absence of or in response to climate policies.

It should be noted that the CO_2 concentration results shown here are somewhat deceptive. By giving results only for one parameterization of climate feedbacks on the carbon cycle they hide very large uncertainties that surround quantification of these feedbacks. Although MAGICC has feedbacks that are similar in magnitude to other carbon cycle models used by IPCC, the Bern model (Joos et al., 2001) and the ISAM model (Kheshgi and Jain, 2003) – see Appendix – some other models have substantially larger feedback effects (Friedlingstein et al., 2006).

Nevertheless, warming uncertainties associated with this particular factor are small compared with uncertainties that arise from our relatively poor knowledge of the magnitude of the climate sensitivity. These uncertainties can be displayed by clicking on the two range buttons on the temperature change output display. The results are shown below …..



Sea level results based on MAGICC for thermal expansion and TAR models (see p. 8) for all other components may be viewed by clicking on the “Sea level” button. The plot below shows the full range of results out to 2400.

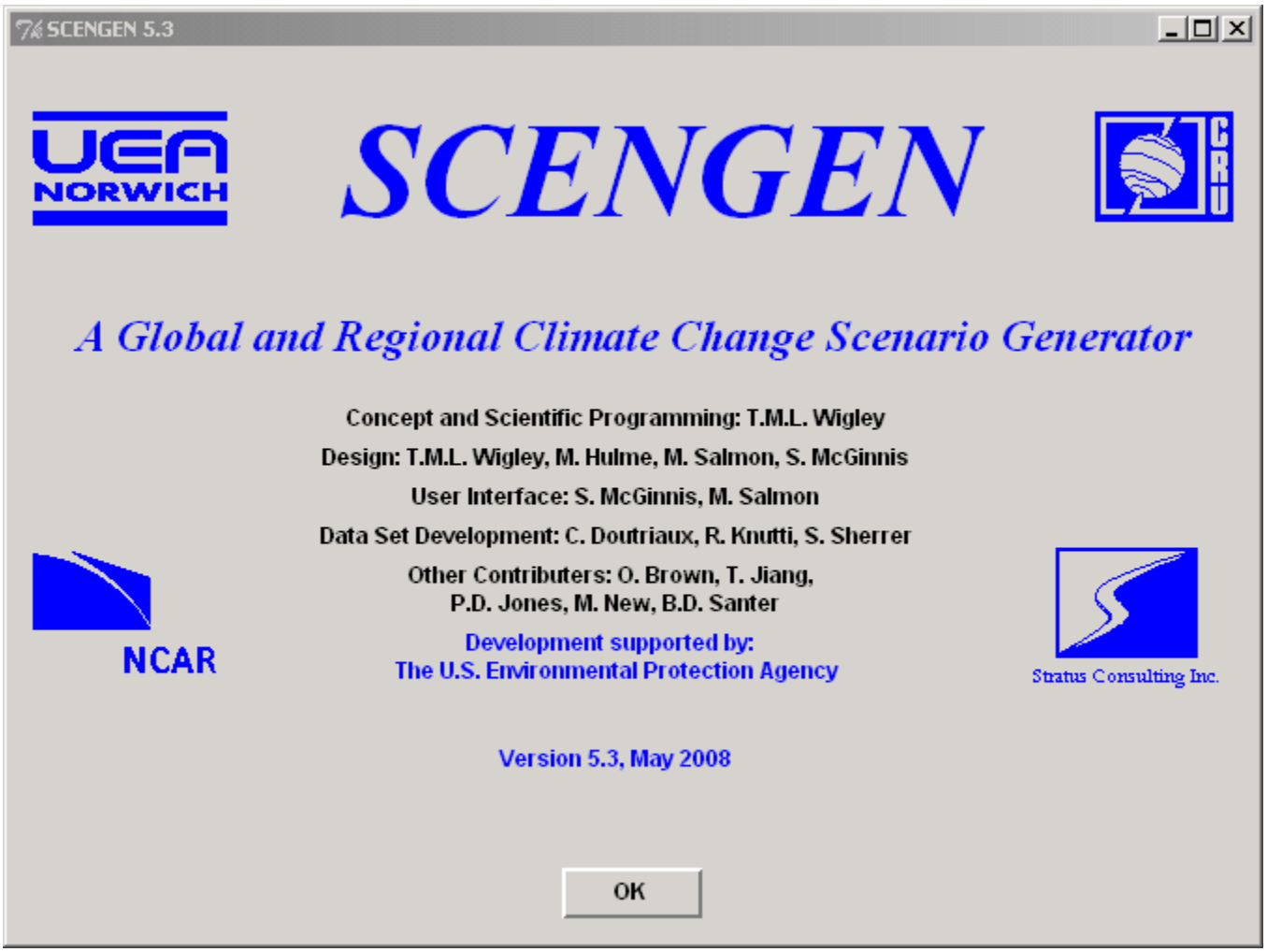


This plot shows both the effect of carbon-cycle climate feedbacks on the central estimate for sea level rise (Best Guess versus User Model results), and an estimate of the overall uncertainty in projections of sea level rise. Carbon-cycle climate feedback effects are relatively small, but overall uncertainties are very large. It should be noted, however, that uncertainties in sea level rise in MAGICC represent the extreme (and likely very low probability) limits where all uncertainties operate in the same direction. The upper bound shown by MAGICC is what would be expected if the climate sensitivity were 6^{o}C and if all ice-melt parameters are set to maximize the ice melt contribution for this sensitivity. The probability of this combination must be considerably less than the probability of a sensitivity as high as 6^{o}C (viz. 5%), but it is impossible to quantify this probability without carrying out a far more sophisticated analysis. Even the central estimates are important, however, as they show the large inertia in the climate components that contribute to sea level rise. Recall that temperatures stabilize in this case, yet sea level continues to rise inexorably.

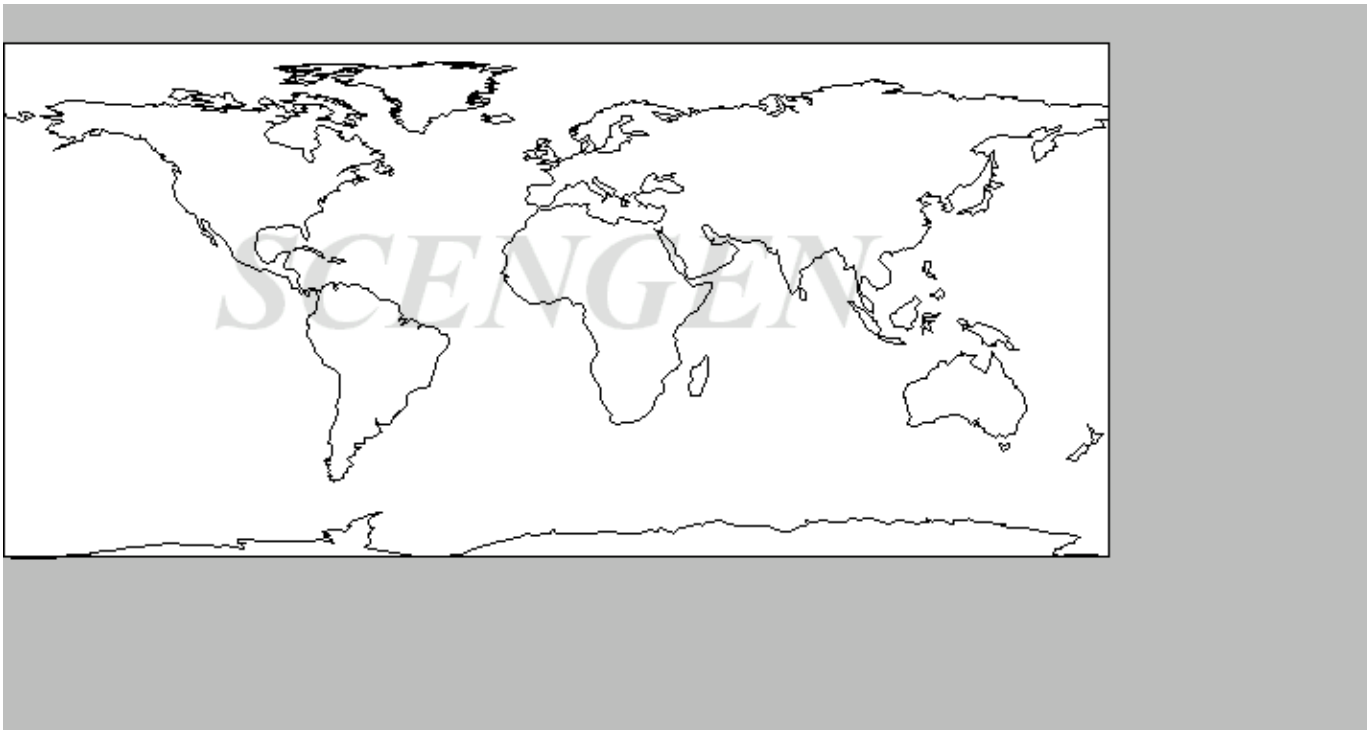
5. Running SCENGEN:

We now move on to explore SCENGEN. The next step then is to go back to the main MAGICC control window, click on the SCENGEN button and then on the “Run SCENGEN” button. This will bring up the SCENGEN title window (see below).

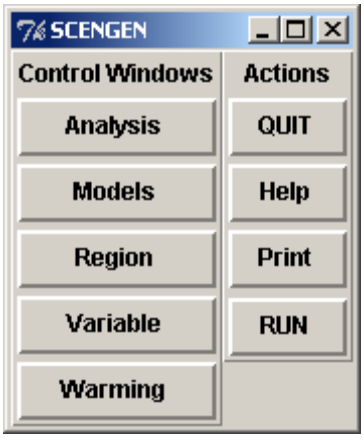
Click on “OK”.


SCENGEN 5.3
UEA NORWICH
SCENGEN
CRU
A Global and Regional Climate Change Scenario Generator
Concept and Scientific Programming: T.M.L. Wigley
Design: T.M.L. Wigley, M. Hulme, M. Salmon, S. McGinnis
User Interface: S. McGinnis, M. Salmon
Data Set Development: C. Doutriaux, R. Knutti, S. Sherrer
Other Contributers: O. Brown, T. Jiang,
P.D. Jones, M. New, B.D. Santer
Development supported by:
The U.S. Environmental Protection Agency
NCAR
Stratus Consulting Inc.
Version 5.3, May 2008
OK

Clicking on OK will bring up a blank map …..



….. and the main SCENGEN selection window.

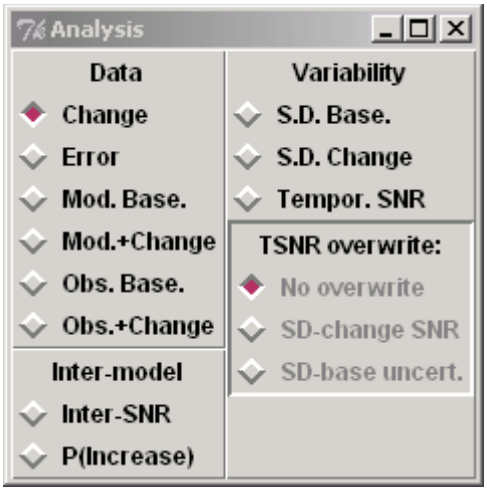


We now work through four examples illustrating some of the capabilities of SCENGEN 5.3.

EXAMPLE 1:

This first example is a comparison of different model results for **changes in the spatial patterns of annual-mean precipitation.** The MAGICC case used is as above, a Reference emissions scenario of A1T-MES and a Policy scenario where CO_2 concentrations follow the WRE450 stabilization profile.

The first step is to click on “Analysis” in the above SCENGEN window. This will bring up the “Analysis” window shown below. The other windows will remain in place and can be moved around to more convenient positions if required.

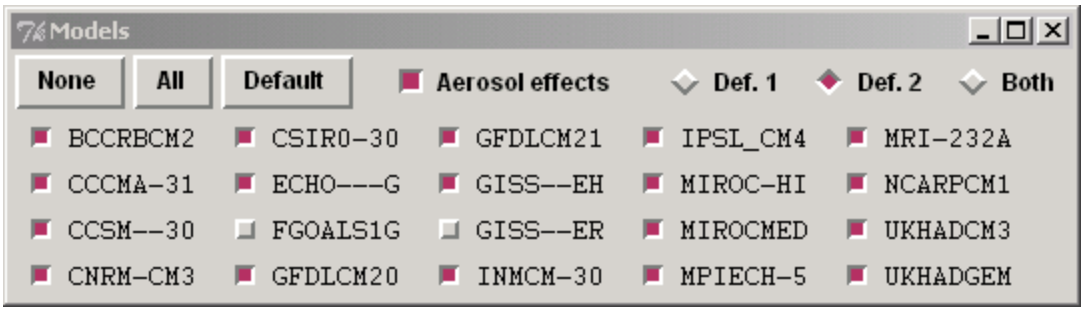


Note that this window has changed from that used in version 4.1. The bottom right panel is new and now allows users to examine inter-model uncertainties in variability: specifically, in the model-mean baseline inter-annual standard deviation, s.d. (“SD-base uncert”), and the model-mean s.d. change (“SD-change SNR”) – see item (10) in Section 3.2 above. Uncertainties in s.d. change are very large – i.e., there are large inter-model differences in projections of variability change, as will be shown below.

Under “Data”, the default selection is “Change” indicating that the analysis to be performed by default will be of changes in the mean state for a particular selected variable. If this button is not lit up, click on “Change” to select an analysis of climate change. The following steps will select: (1) the AOGCMs to be used (displayed results are for the average across the selected models); (2) the analysis region (we will use the full globe); (3) the analysis variable and season (we use annual precipitation); and (4) the analysis year, emissions scenario, and MAGICC parameter set. These selections (including the type of analysis – “Change”, etc.) may be made in any order.

We first select the models to be used to define the change. As noted above, the displayed results will give the average change over the selected models. A crucial and unique aspect of SCENGEN is that averages across models are based on **normalized** results (following the original implementation of this idea in Santer et al. (1990)). Using normalized results ensures that each model pattern of change receives equal weight and the average is not biased towards

models with high climate sensitivity. To select the models to use, go back to the SCENGEN window and click on “Models”. This will bring up the window shown below.

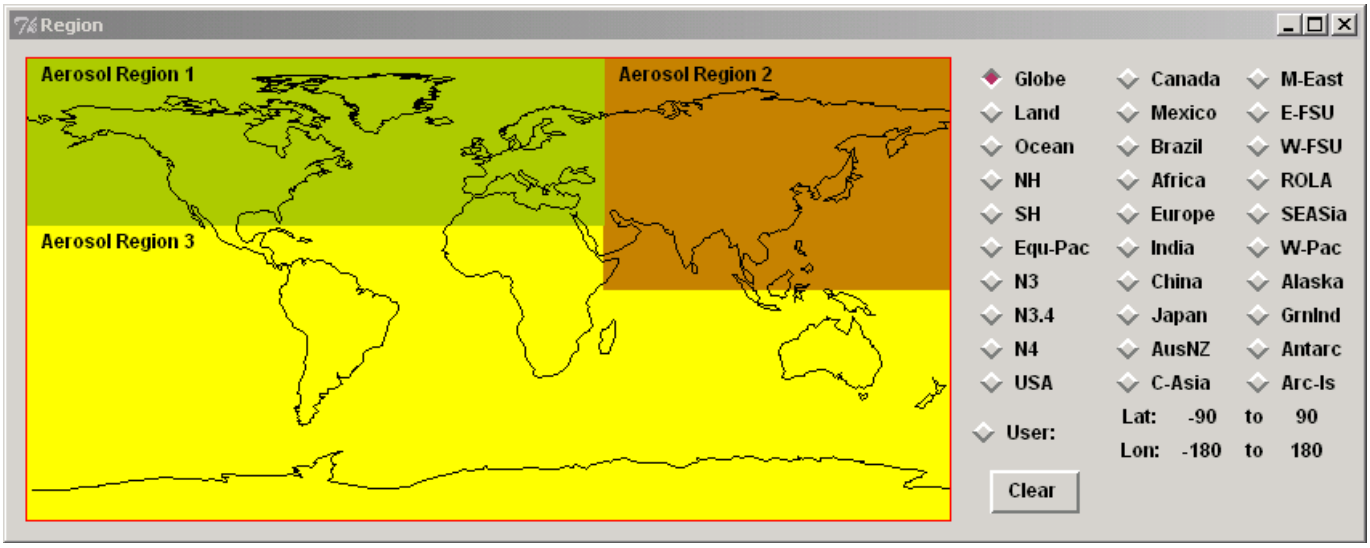


Certain models (a selection of U.S. models) will be lit up as default. The user can select any set of models, from a single model to all models, and SCENGEN will produce results averaged over the selected models. For further information on these models, see the IPCC Fourth Assessment Report (Randall and Wood, 2007)

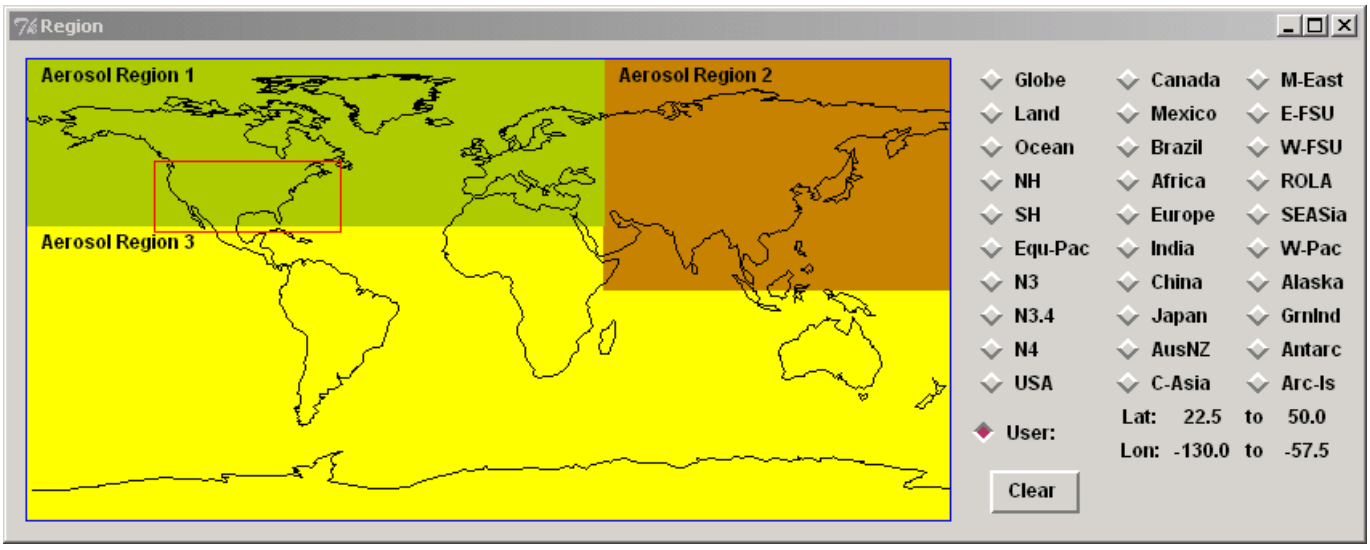
For the present example we use all models except FGOALS and GISS-ER (for reasons stated above). To get the above selection, the user should click on “All” and then click on FGOALS and GISS-ER to de-select these two models. Next, the user has the option of using Definition 1 or Definition 2 changes. Def. 1 uses the difference between the start and end of a perturbation experiment. Def. 2 uses the difference between the perturbed state and the control climate at the same time. If a model has any spatial drift (and most models do) then Def. 2 is a way of removing this drift (under the justifiable assumption that the drift is approximately common to both the perturbed and control runs) – normally one should use Def. 2.

Next, the user must decide whether or not to include the spatial effects of aerosols. Normally, these effects should be included (which is done by clicking on the “Aerosol effects” button). The option not to include aerosol effects is to allow the user to determine how important these effects are. The “Models” window shown above corresponds to these selections.

Next, return to the SCENGEN window and click on “Region”. The map below will be displayed.



The map shows the regions used for the breakdown of SO_2 emissions in the MAGICC emissions files, together with a set of analysis region selections. (Emissions from ocean and air transport are divided equally over the three regions.) The default region is the whole globe, and this is what will be used in the present examples. The user can select from a range of "hard-wired" regions, or can mouse out a rectangular latitude/longitude region on the map. To do this, click on "User" and use the mouse to define a region. The latitude/longitude domain will be shown numerically on the right. The selected region appears as a red rectangle – see the map below -- and the domain limits appear on the bottom right of the window. (Note that the hard-wired regions are generally not rectangular.) For user-selected rectangular regions the latitude and longitude ranges shown correspond to the full domain. Latitude values are in degrees north from the equator, and longitude values are in degrees east.



Selecting a grid-box region means that most calculations will be carried out specifically for that region. This includes area averages for the selected variable (see below), and a range of other statistics. These results are not displayed, but are given in tabulated form in various output files in the ENGINE/IMOUT or ENGINE/SDOUT directory (see Table 5 above).

After experimenting with the user region option, return to using the whole globe by clicking on “Clear” and then “Globe”.

Now return to the SCENGEN window and click on “Variable”. The “Variable” window (below) will appear. The default is annual-mean temperature. Click on “Ann” to see the other season options, and then return to “Ann”. Next click on “Precipitation”, since this is the variable we will use for the examples. Note that the “Reverse” light will come on, since the standard rainbow color scheme for precipitation (red for dry to blue for wet) is the opposite of that usually used for temperature (blue for cold to red for hot). This can be de-selected by clicking on the “Reverse” button.

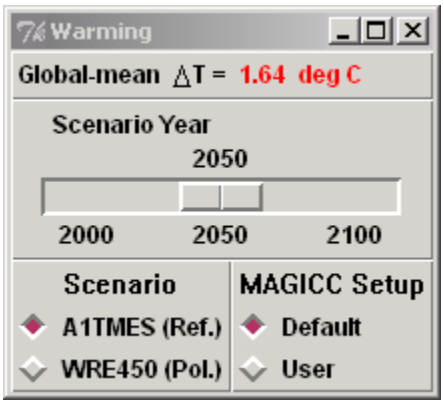
This window gives the user the option to use linear or power law (exponential) scaling. The latter is a way of avoiding physically unrealistic results that can (albeit only rarely) occur with linear scaling if the global-mean warming is large. For these examples we will stick with linear scaling. For precipitation changes, exponential scaling is preferred. Users should experiment with both scaling methods to see the differences.

There are two new options on the “Variable” window. First there is a spatial smoothing option that replaces all output fields by an area-weighted 9-box smoothed field (see item (5) in Section 3.2 above). Second, there is now a range of color palette schemes and an improved method for choosing contour levels and intervals (see item (6) in Section 3.2).

Selecting the spatial smoothing option means that, if a single 2.5 by 2.5 degree grid box is selected as the region, the results will be area averages over the nine grid boxes centered on the selected grid box. If spatial smoothing is selected, this will be applied to all output array files and displays.

To change the palette, click on the “rainbow” button. To change the contour levels to span the range of grid-box values better, click on the Min/Max button.

Return again to the SCENGEN window and click on “Warming”. The following window will appear …..

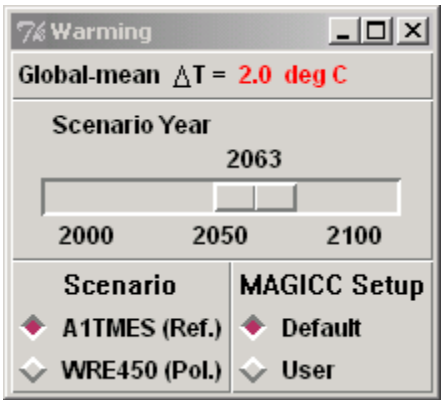


This is where the user selects the following:

(1) the emissions scenario, either the Reference or the Policy case. The names displayed show only the first nine letters of the headers on the emissions files.
(2) the scenario year (i.e., the central year for a climate averaging interval of 30 years, as indicated by the length of the slider bar. The default year is 2050, as shown.
(3) a particular configuration for the MAGICC model, Default (i.e., “best guess”) or User.

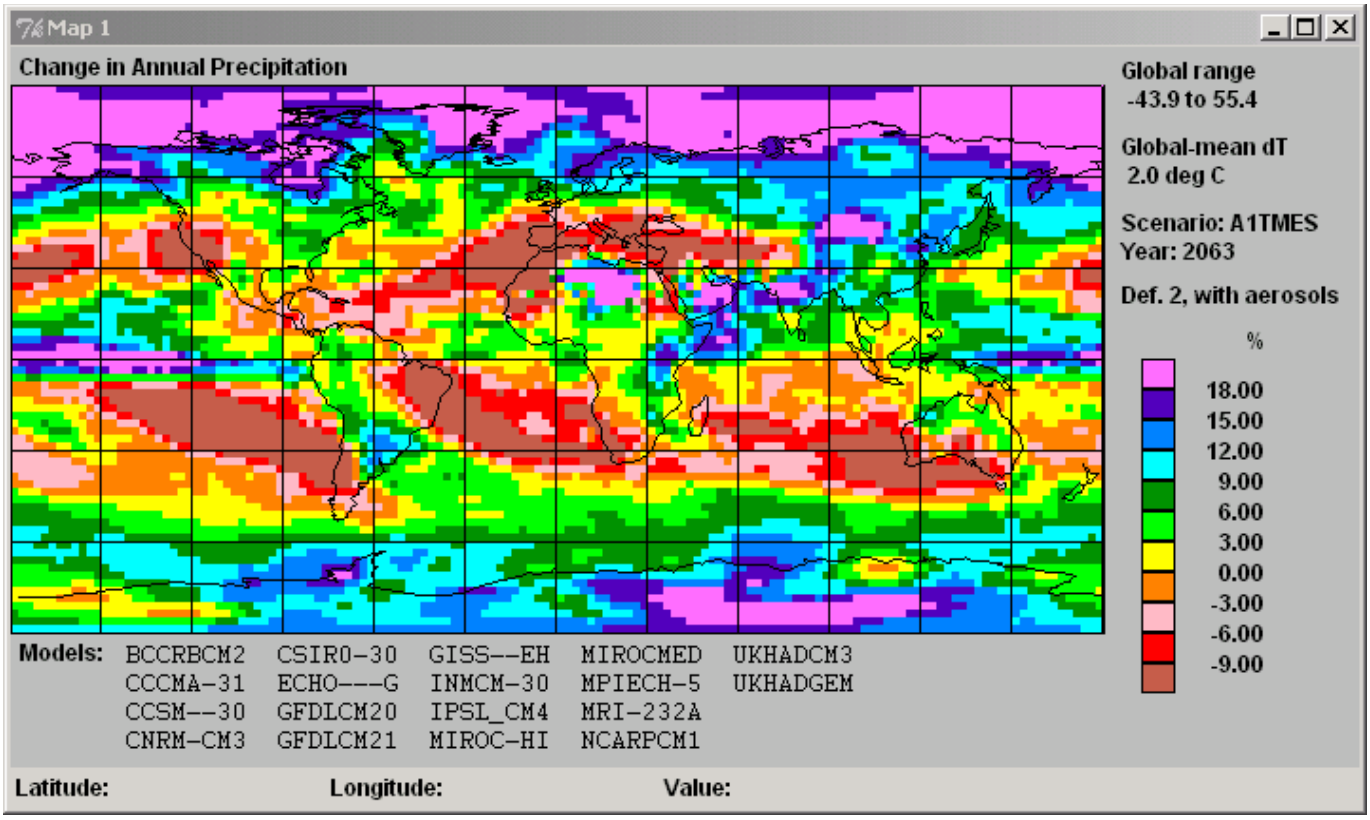
These factors determine the global-mean temperature change from 1990 to 2050 (red 1.64 degC at top of window in this case) that is used for scaling the normalized patterns of change. Within the code, this global-mean temperature change is broken down into four components (a ghg component, and aerosol components for the SO_2 emissions in the three emissions regions shown above) and these are used as weights for the pattern scaling algorithm.

For the present examples we will use the default emissions scenario (A1T-MES, the selected Reference scenario), and default parameters for MAGICC. We also slide the temperature bar across to 2064 to give a warming of 2 degC – see window below.

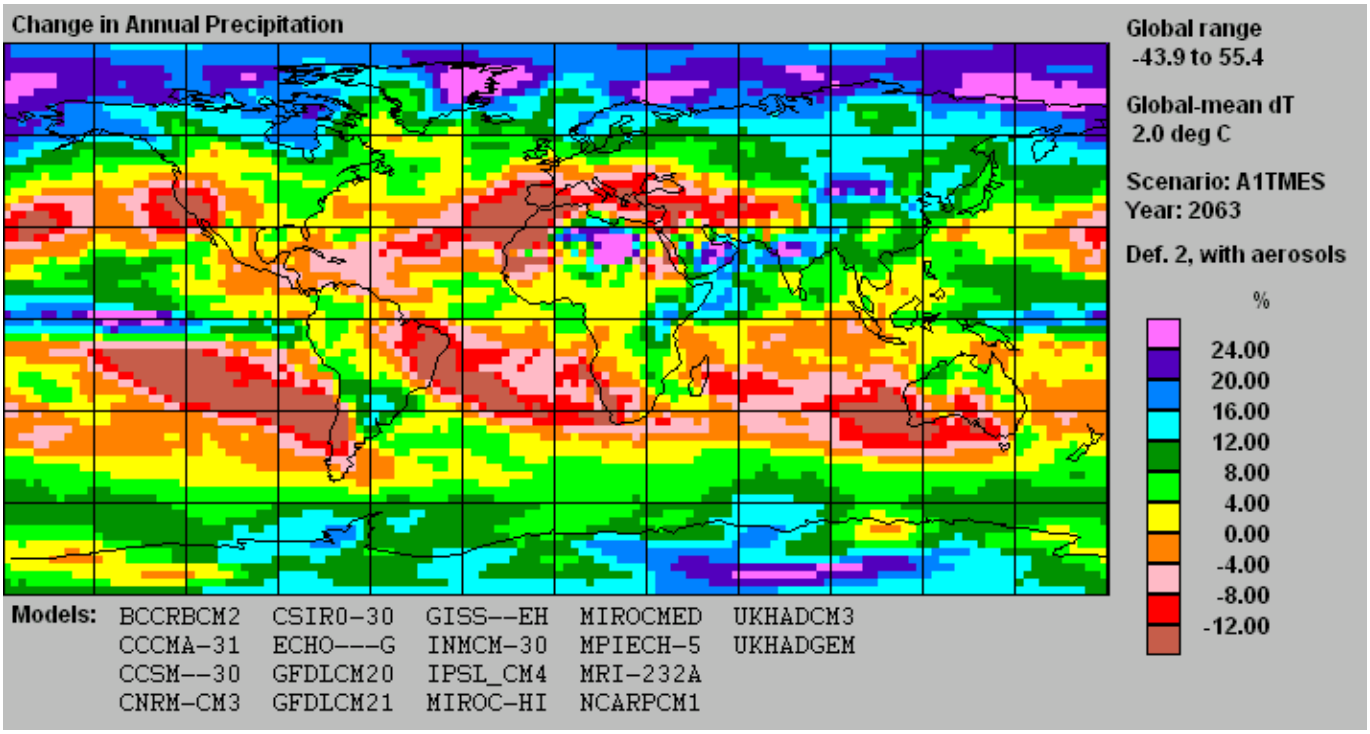


At this stage, all necessary user selections for SCENGEN have been made.

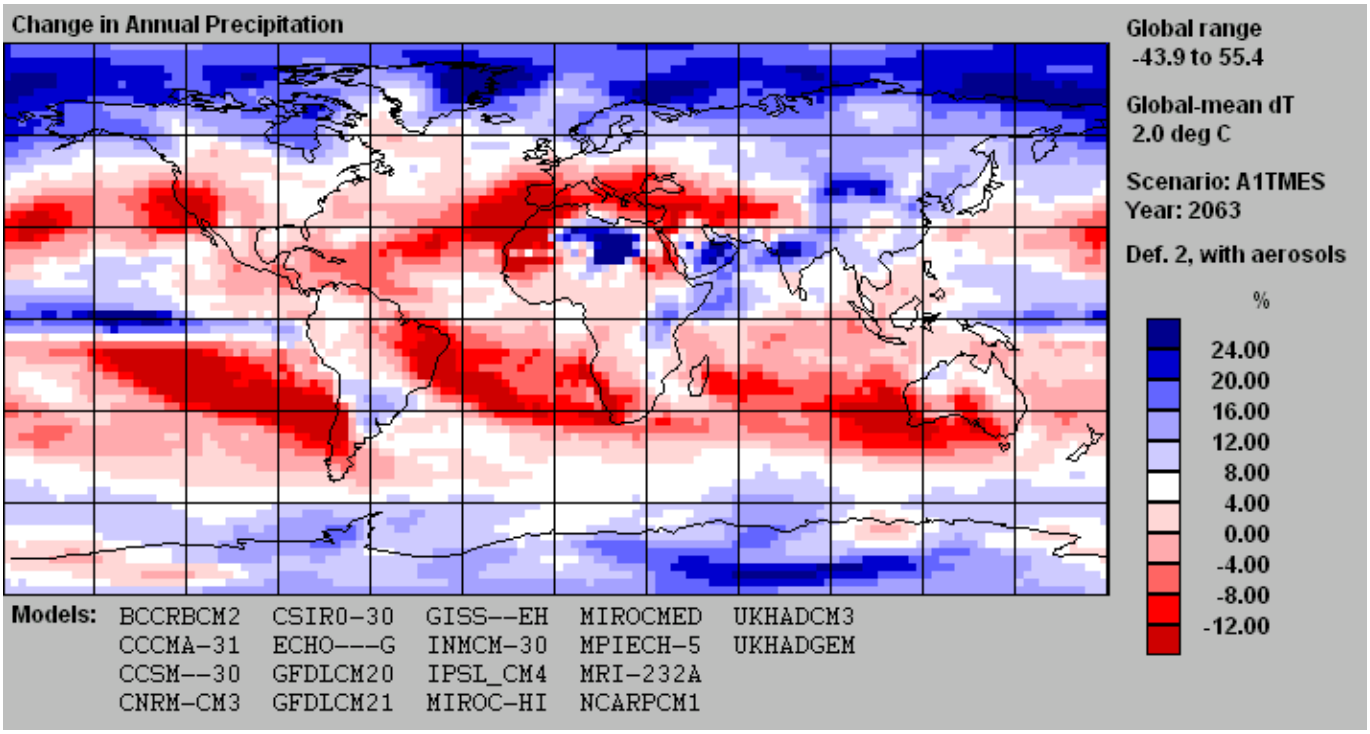
Return now to the SCENGEN window and click on “RUN” to run the SCENGEN software. After a short time, a map will appear – see below. This shows the change in annual-mean precipitation for the 30-year interval centered on 2064 (for the A1T emissions scenario, and “best guess” climate model parameters in MAGICC) averaged over all 18 selected AOGCMs.



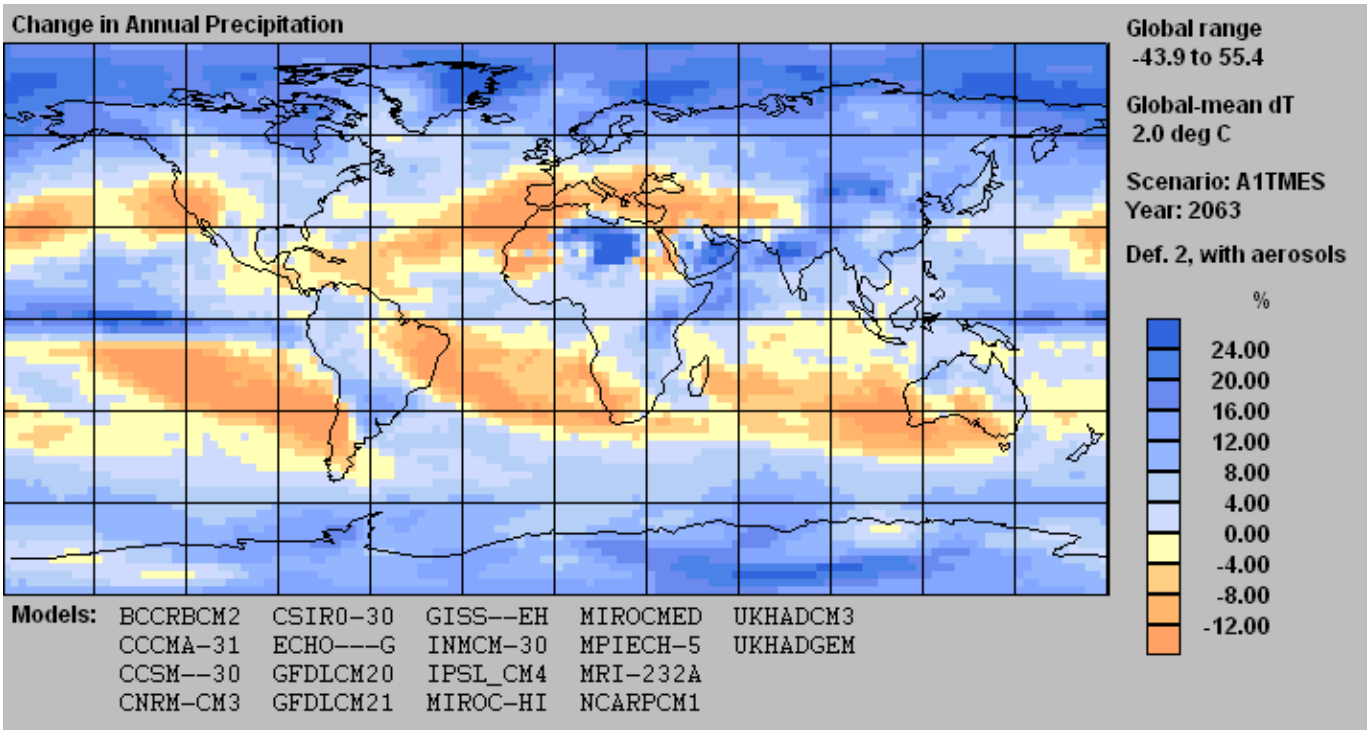
The default display is as shown above. Mousing over the map will show specific grid-box values in the lowest panel of the display. We now illustrate other possible displays. First, we use the “Min/Max” option on the “Variable” window, which will ensure that approximately 5% of the grid-box values will lie above (below) the highest (lowest) contour level.



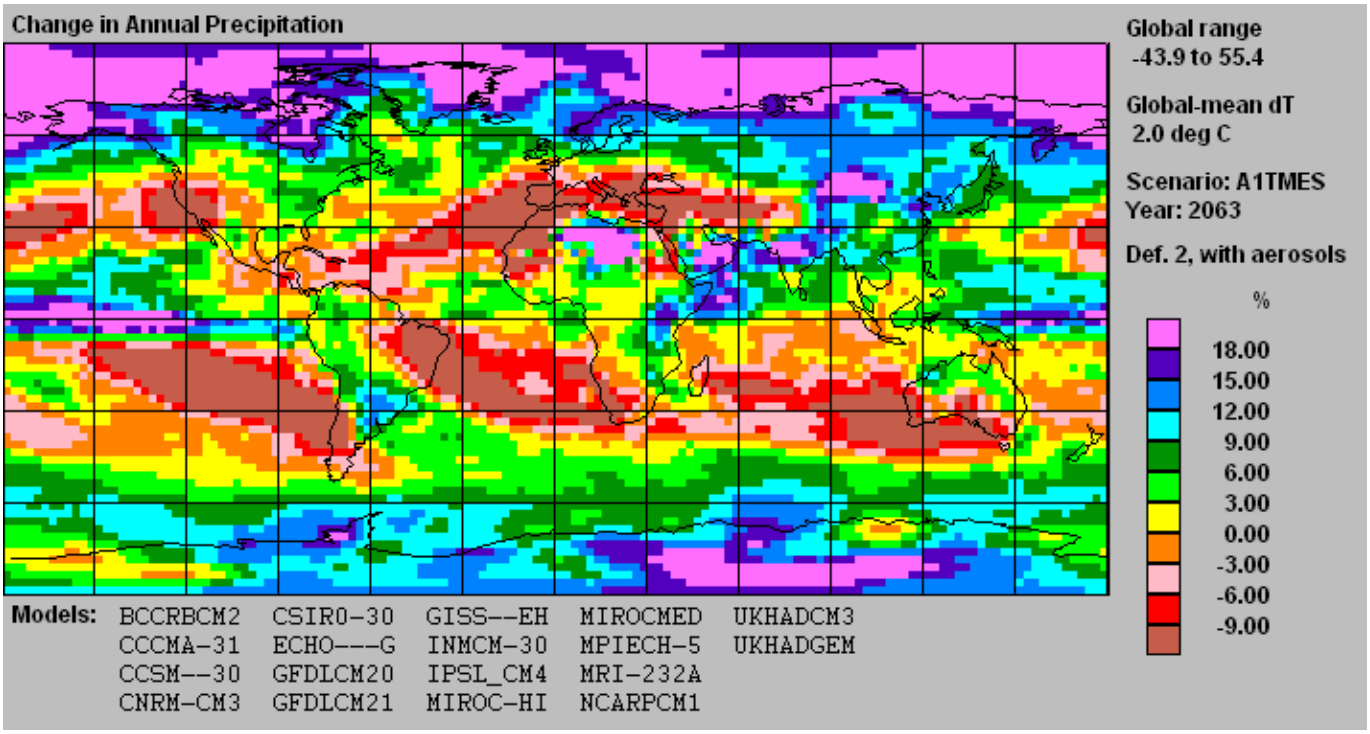
(In the above and subsequent displays the top and bottom parts of the full panel have been deliberately suppressed.) Next, we retain the Min/Max contouring and select the red-blue color palette – below.

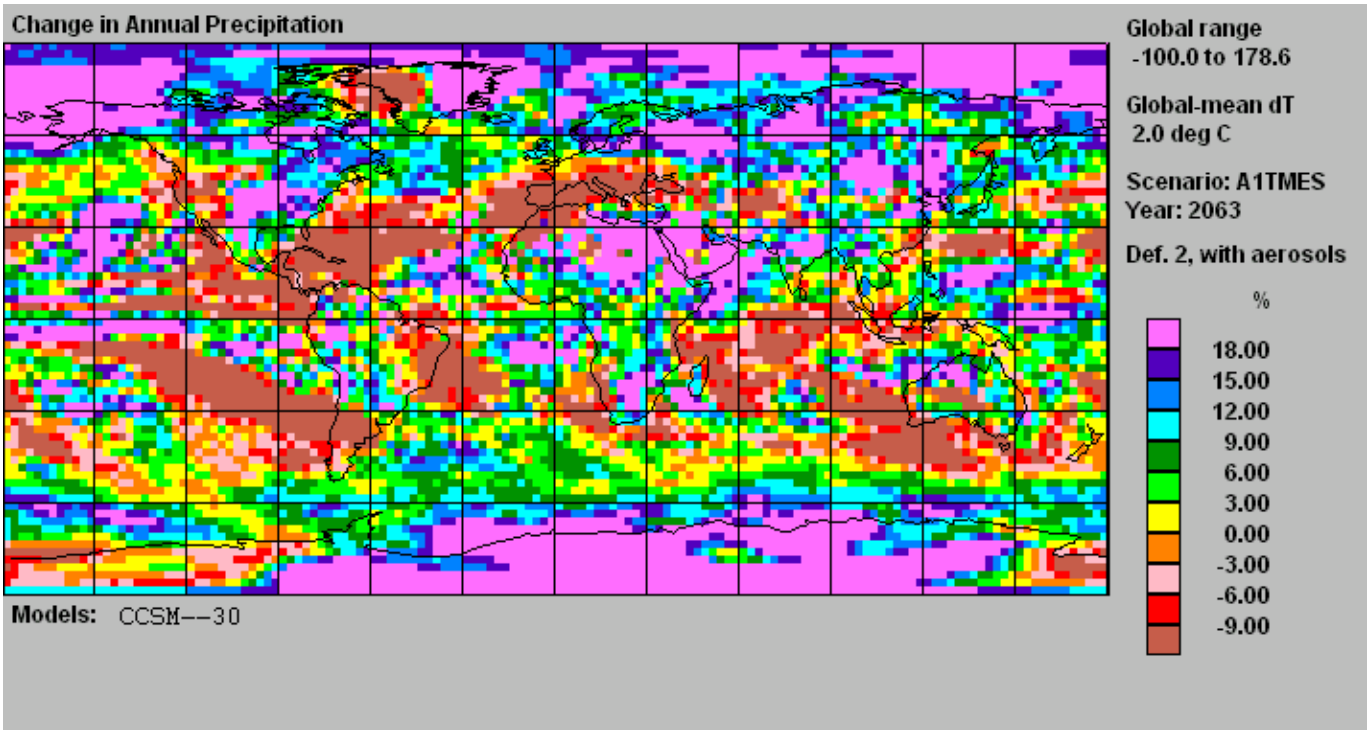


Finally we select the AR4 color palette. This palette has the yellow/blue boundary as the zero contour level.



We now compare the multi-model average results with those for a single AOGCM. For the single model we choose NCAR's Community Climate System Model (CCSM3). We show below the multi-model result for default contouring and palette (repeated from above) with the CCSM3 result immediately below this.





It can be seen that there are clear similarities between the multi-model mean pattern and the CCSM3 result – although the latter pattern is, understandably, more noisy. In both cases, precipitation increases in high latitudes and decreases in subtropical regions and in places like the Mediterranean Basin and southwest Australia. Overall, changes in CCSM3 are much larger than in the multi-model mean, implying that there are cancelling effects when a number of models are averaged.

The visual similarity, however, is deceptive, and the overall pattern correlation between CCSM3 changes and the mean of the remaining 17 selected models is quite small (r = 0.372). Pattern correlation results such as this may be found in OUTLIERS.OUT (in folder …ENGINE/IMOUT), for which an extract is given below. (To produce this Table, you will have to go back to the original 18-model selection and re-run SCENGEN.)

Note that CCSM3 precipitation changes are biased high relative to other models ("BIAS" in the Table below is model-i minus the mean of the remaining models for 1^{o}C global-mean warming). Note also that the results in the Table below do not correspond precisely to the maps above, since OUTLIERS results are based solely on the normalized precipitation changes (i.e., they do not account for scaling up to the MAGICC global-mean temperature change, nor do they account for aerosol effects on precipitation change). Nevertheless, these OUTLIERS results provide a good indication of the more general pattern similarities.

COSINE WEIGHTED STATISTICS

MODEL	CORREL	RMSE %	BIAS %	CORR-RMSE %	NUM PTS
BCCRBCM2	.442	7.050	.420	7.038	10368
CCCMA-31	.562	5.997	-.171	5.994	10368
CCSM--30	.372	8.507	1.002	8.448	10368
CNRM-CM3	.312	7.945	.175	7.943	10368
CSIR0-30	.351	9.214	.616	9.193	10368
ECHO---G	.327	8.519	-.861	8.475	10368
GFDLCM20	.456	10.139	.510	10.126	10368
GFDLCM21	.402	11.190	-2.166	10.979	10364
GISS--EH	.396	7.854	.515	7.837	10368
INMCM-30	.424	7.049	.178	7.047	10368
IPSL_CM4	.397	10.135	-1.085	10.077	10358
MIROC-HI	.523	5.478	.539	5.452	10368
MIROCMED	.599	5.624	-.219	5.620	10368
MPIECH-5	.342	15.497	.870	15.473	10361
MRI-232A	.365	10.688	.257	10.685	10363
NCARPCM1	-.067	15.157	.822	15.135	10368
UKHADCM3	.424	10.049	-.940	10.005	10368
UKHADGEM	.522	6.514	-.119	6.513	10368

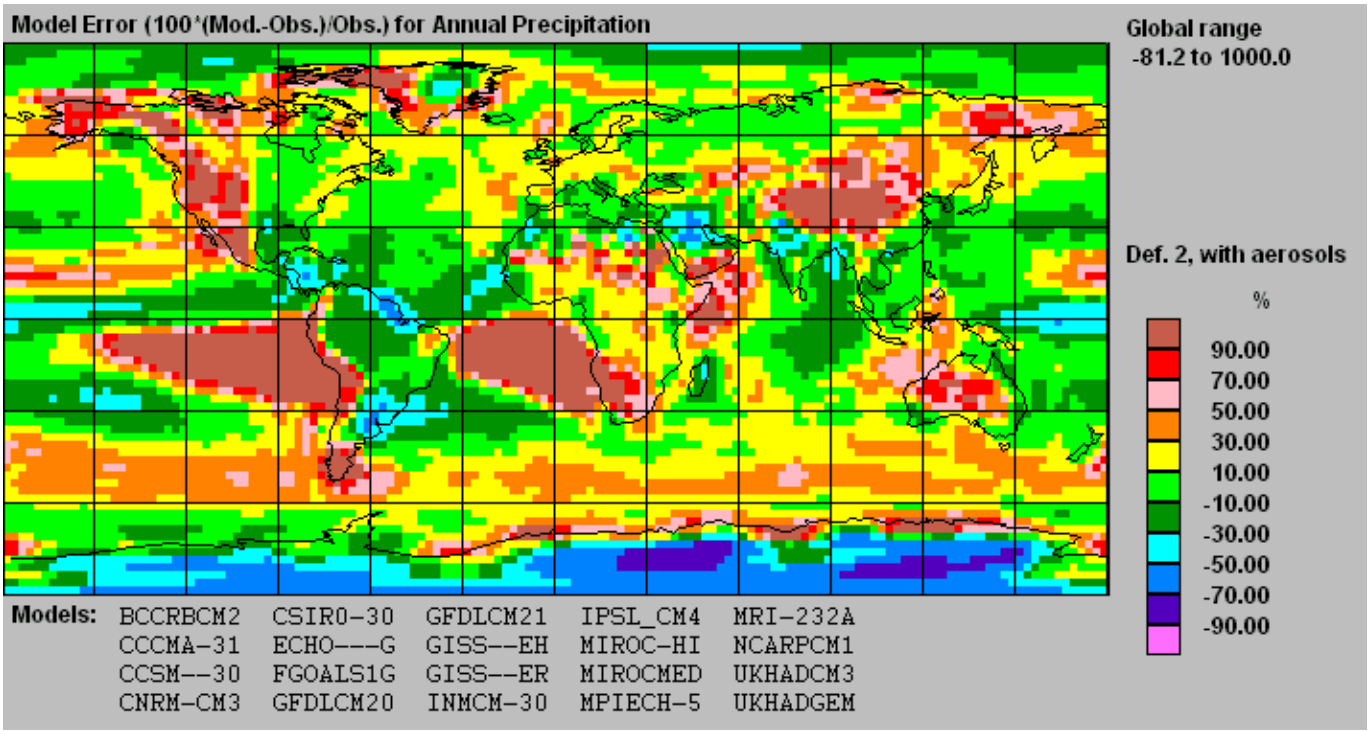
The above results provide a strong indication that there are large inter-model differences between AOGCM precipitation change projections. A further indication of these large inter-model differences can be obtained using Inter-SNR and P(Increase) – see these buttons on the "Analysis" window. We explore these further below.

EXAMPLE 2:

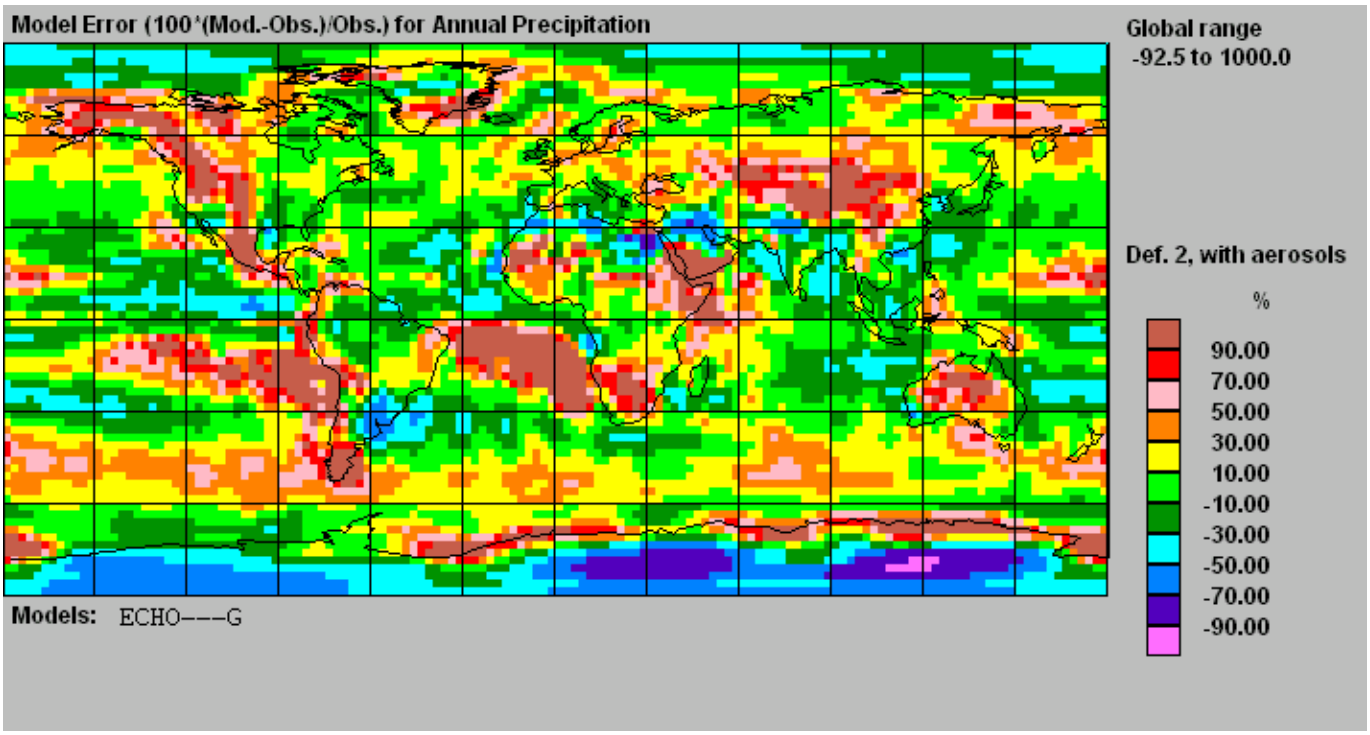
In this example we investigate **model errors in simulating present-day patterns of precipitation and mean sea level pressure (MSLP)** relative to the observed climate. For precipitation, we will consider the model average, and two individual models. For the individual models, to span the range of model skill in simulating present-day annual precipitation we choose the best and worst models by making use of results in VALIDN.OUT. Part of this output (that for cosine-weighted statistics) is shown in the Table below. (To produce this we have run SCENGEN with all models selected, including FGOALS and GISS-ER.) The best model here (in terms of the global pattern correlation) is ECHO-G, while the worst is NCAR's PCM. (Note that the ECHO results are somewhat deceptive, because this is a flux-corrected model.)

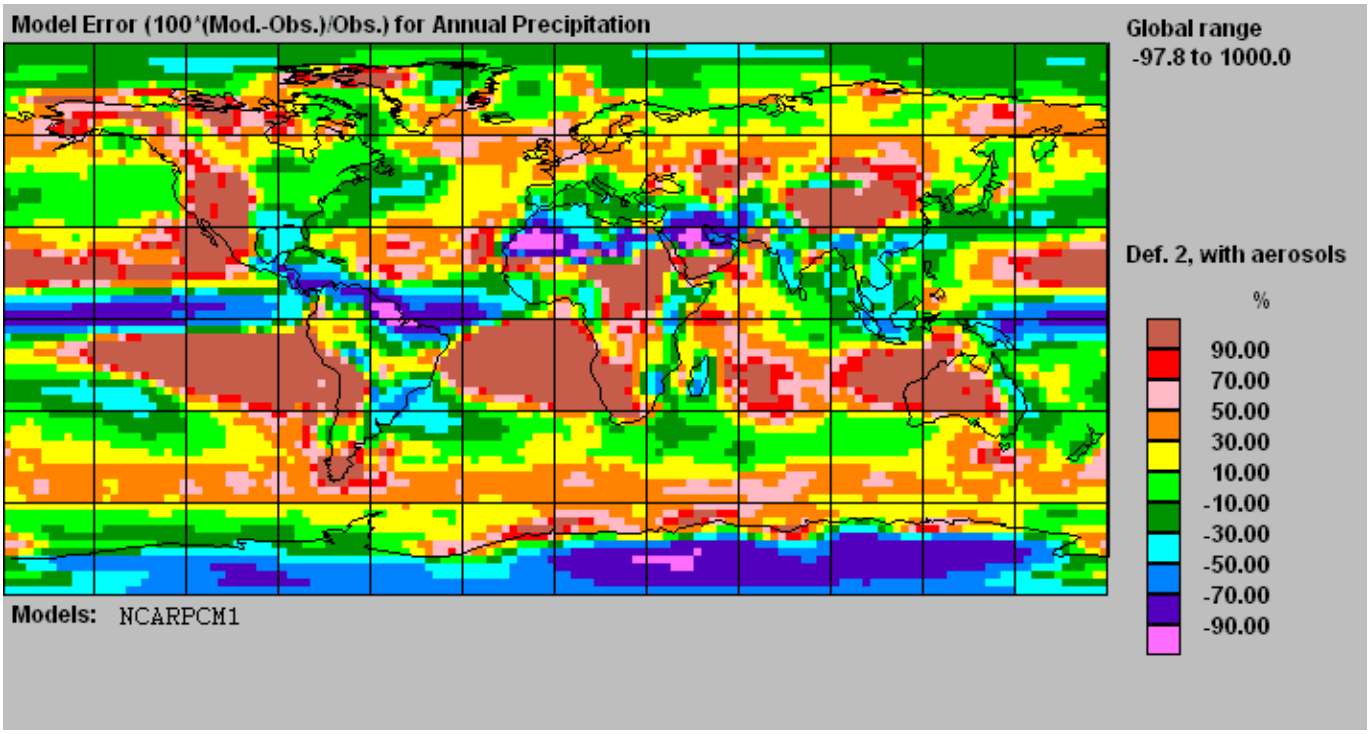
```
*** 20 MODELS : VARIABLE = CMAP PRECIP : SEASON = ANN ***

 MODEL VALIDATION: COMPARING MODEL-i BASELINES WITH OBSERVED DATA
 MODEL BASELINE FROM CONTROL RUNS

 BIAS IS DIFFERENCE IN SPATIAL MEANS: MOD MINUS OBS
 CORR-RMSE IS RMSE CORRECTED FOR BIAS

 RK INDEX, BASED ON REICHLER & KIM (2008), DIMENSIONLESS
  INDEX = AREA AVERAGE OF [(MOD-i MINUS OBS)**2]/[(MOD-i S.D.)**2)]

 AREA SPECIFIED BY MASK. MASKFILE = MASK.A : MASKNAME = GLOBE

 COSINE WEIGHTED STATISTICS
    MODEL   CORREL     RMSE       BIAS  CORR-RMSE   RK INDEX    NUM PTS
                     mm/day     mm/day     mm/day
 BCCRBCM2     .793    1.311       .307      1.275     43.960      10368
 CCCMA-31     .888     .949      -.010       .949     21.286      10368
 CCSM--30     .797    1.327       .160      1.317     36.782      10368
 CNRM-CM3     .772    1.438       .540      1.333     19.566      10368
 CSIR0-30     .814    1.209      -.161      1.198     94.574      10368
 ECHO---G     .910     .864       .128       .854     13.766      10368
 FGOALS1G     .816    1.226       .307      1.187     15.120      10368
 GFDLCM20     .868    1.099       .091      1.095     22.909      10368
 GFDLCM21     .857    1.149       .215      1.128     25.030      10368
 GISS--EH     .733    1.512       .340      1.473     31.909      10368
 GISS--ER     .774    1.430       .297      1.399     34.008      10368
 INMCM-30     .700    1.606       .116      1.601     17.914      10368
 IPSL_CM4     .808    1.269      -.090      1.266     55.101      10368
 MIROC-HI     .800    1.340       .281      1.311     28.908      10368
 MIROCMED     .833    1.162       .035      1.162     28.548      10368
 MPIECH-5     .808    1.351       .247      1.328     18.631      10368
 MRI-232A     .886     .967      -.084       .963     19.226      10368
 NCARPCM1     .665    1.715       .343      1.680     40.144      10368
 UKHADCM3     .858    1.256       .230      1.235     24.384      10368
 UKHADGEM     .797    1.614       .385      1.568     44.852      10368
 MODBAR       .910     .870       .184       .850    120.441      10368
```

First, to clear the screen, either minimize or delete any existing maps. Now return to the Analysis window and select "Error". (Note that the "Reverse" palette on the "Variable" window will de-select, as this is the default only for precipitation.) Annual precipitation has already been selected from the previous example. Now click on RUN in the SCENGEN window, and the map below will appear.



This map shows the percentage error in annual precipitation averaged over the 18 selected models. On average, models are biased wet in the South Pacific and South Atlantic subtropical highs, western North America, the interior parts of Australia, and a few other regions. Models tend to be biased dry in the tropical Pacific and Antarctica. We now select the two chosen models – see the two maps below …



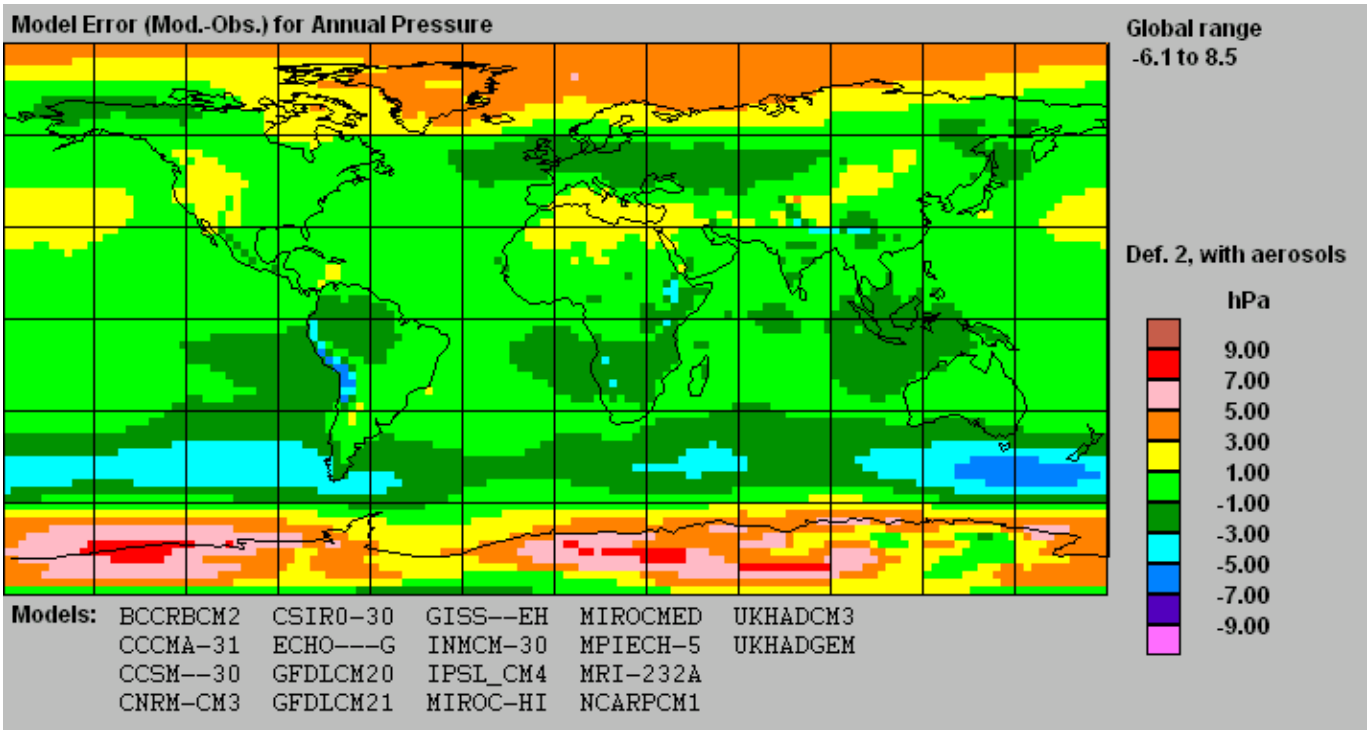


Error patterns for both of these models are similar to each other and both are similar to the model-mean result.

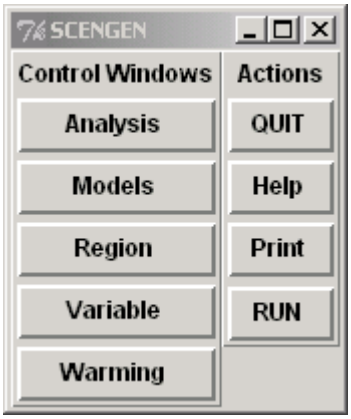
It is clear that, when expressed as a percentage, there are appreciable errors in most if not all AOGCMs. Some of these results are deceptive, however. Many of the largest errors occur in regions of low precipitation, such as over the oceanic sub-tropical highs: in absolute terms these errors are quite small. Other areas of large percentage error (e.g. the western sides of North and South America) occur where model orography is much smoother than in the real world – although it is interesting that the error fields show that the models tend to over-estimate precipitation in these regions. There are also considerable uncertainties in the observational data.

Further validation statistics are given in the ENGINE/IMOUT directory (VALIDN.OUT). VALIDN.OUT gives results only for the selected models and the selected region. This is the whole globe here, but it is often of interest to see how well the model(s) perform over a smaller region.

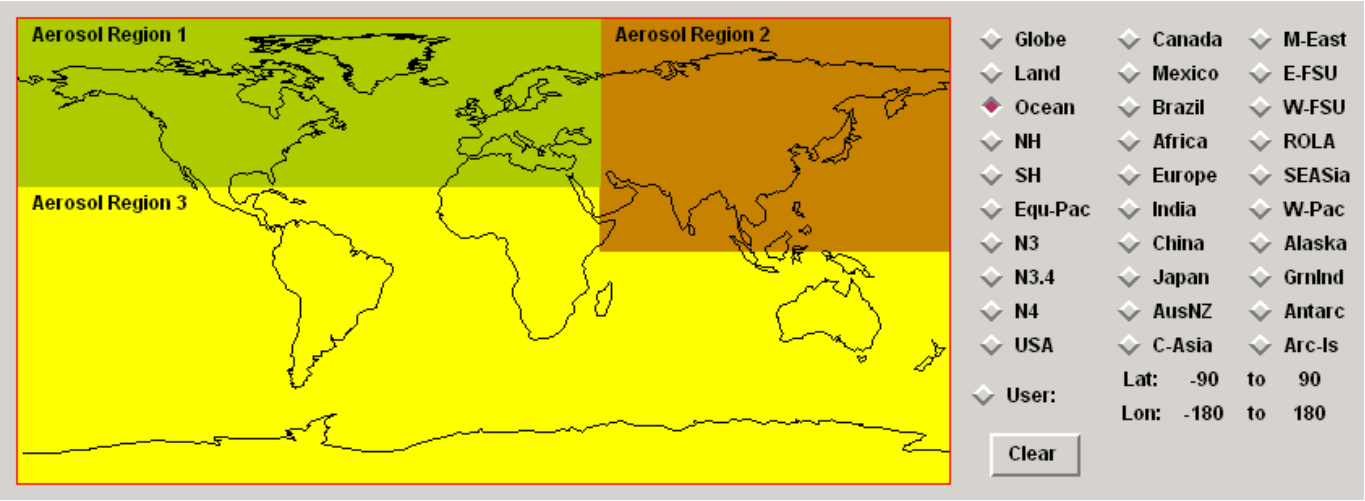
As a second “Error” example, we will now consider errors in model baseline mean sea level pressure (MSLP). First clear the existing maps, select all models except FGOALS and GISS-ER again, and then click on “pressure” in the “Variable” window. (Note that Ann remains selected.) Then click on RUN to get the following map …



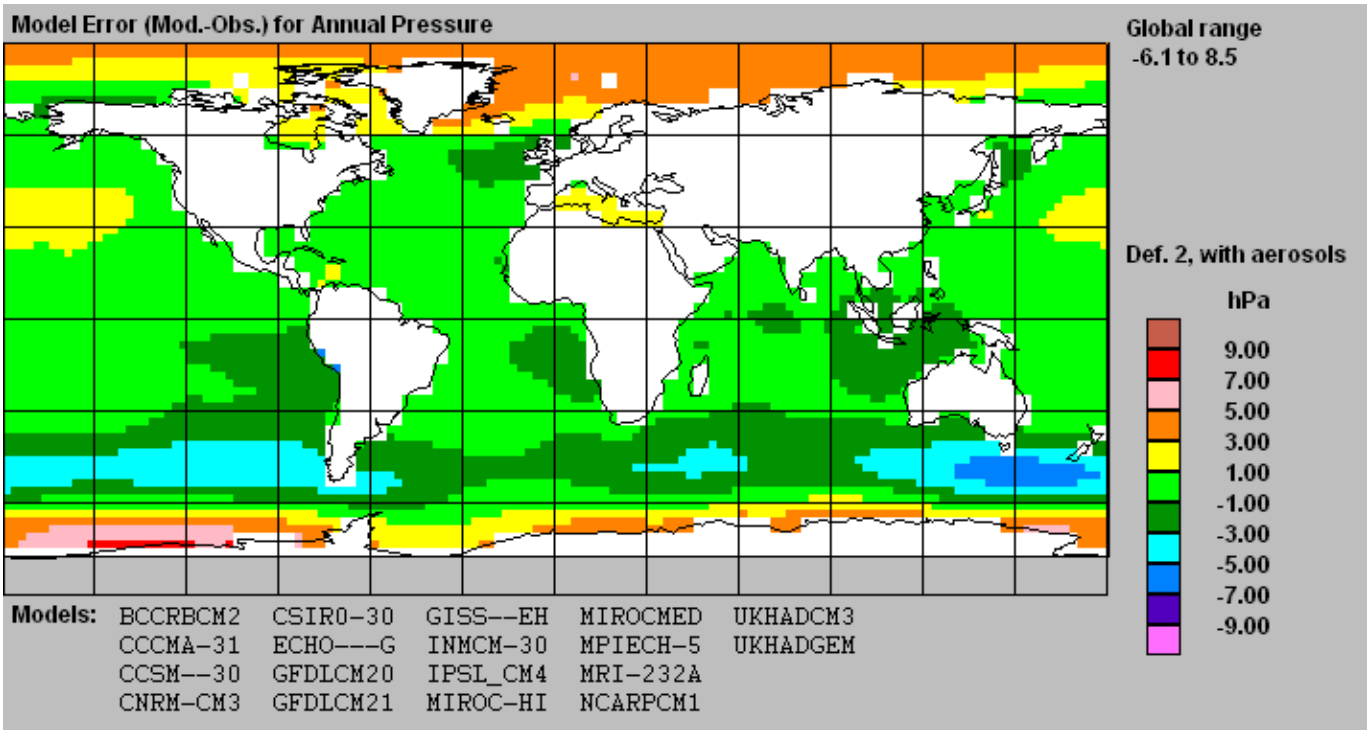
The error for MSLP (and for temperature) is expressed in absolute units rather than relative units as used for precipitation. For assessment of MSLP skill, however, there is an important additional consideration. Because pressure data are reduced to sea level, model/observed differences can arise because of this reduction, in turn because model orography is considerably smoothed relative to real-world orography. There are also differences in the way different models reduce surface data to sea level, and these methods may differ from the reduction method employed by the ERA40 observed data base we employ. For this reason, validation of MSLP should consider only ocean areas. To do this, click on Region in the SCENGEN window …



This opens the window displayed below. Then select “Ocean” from the list of hard-wired regions/



After clicking on RUN we obtain …



It can be seen that there are model MSLP biases even over ocean areas, but they exceed 3 hPa only in high latitudes and around the Antarctic circumpolar trough. Further model-specific insights into these errors can be obtained from the VALIDN.OUT file. Part of which is shown below.

*** 18 MODELS : VARIABLE = MSLPRESSURE : SEASON = ANN ***

MODEL VALIDATION: COMPARING MODEL-i BASELINES WITH OBSERVED DATA

NOTE: BECAUSE OF DIFFERENCES IN OROGRAPHY AND REDUCTION TO SEA LEVEL,
VALIDATION OF MSLP SHOULD USE THE OCEAN-ONLY MASK.

MODEL BASELINE FROM CONTROL RUNS.

BIAS IS DIFFERENCE IN SPATIAL MEANS: MOD MINUS OBS

CORR-RMSE IS RMSE CORRECTED FOR BIAS

RK INDEX, BASED ON REICHLER & KIM (2008), DIMENSIONLESS.
INDEX = AREA AVERAGE OF SQRT[((MOD-i MINUS OBS)**2)/(OBS-S.D.**2)]

AREA SPECIFIED BY MASK. MASKFILE = MASK.C : **MASKNAME = OCEAN**

COSINE WEIGHTED STATISTICS

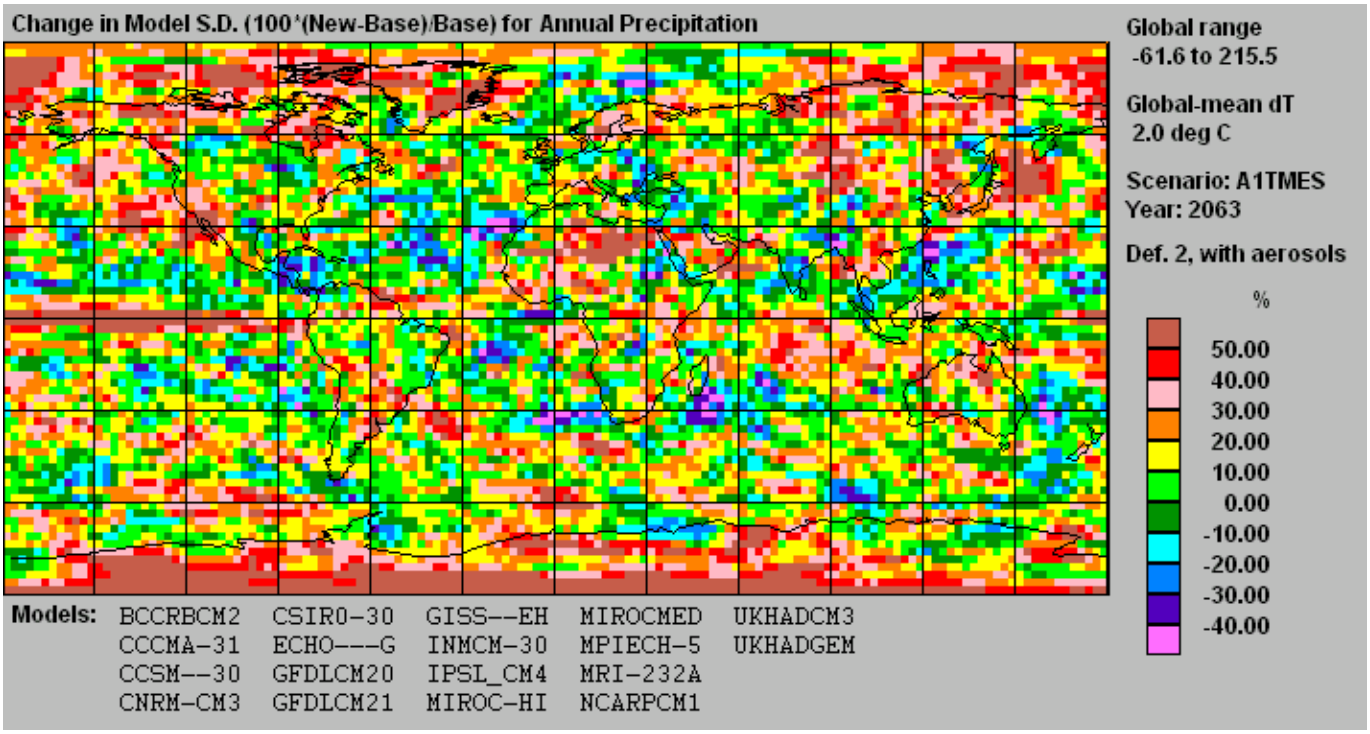
MODEL	CORREL	RMSE hPa	BIAS hPa	CORR-RMSE hPa	RK INDEX	NUM PTS
BCCRBCM2	.930	3.635	1.046	3.482	1.864	6560
CCCMA-31	.961	2.465	-.061	2.464	2.187	6560
CNRM-CM3	.908	4.155	.417	4.134	2.512	6560
CSIR0-30	.978	2.672	-.036	2.672	2.193	6560
GFDLCM20	.949	2.825	-.471	2.786	1.621	6560
GFDLCM21	.984	1.647	-.472	1.578	1.638	6560
GISS--EH	.935	6.557	-5.455	3.638	10.047	6560
INMCM-30	.972	2.119	.240	2.105	1.964	6560
IPSL_CM4	.869	4.325	-.503	4.295	2.314	6560
MIROC-HI	.967	2.960	-.151	2.956	2.838	6560
MIROCMED	.957	2.984	-.697	2.902	2.285	6560
ECHO---G	.969	2.306	-.175	2.299	1.770	6560
MPIECH-5	.984	1.538	-.086	1.535	1.109	6560
MRI-232A	.968	2.210	-.144	2.205	1.532	6560
CCSM--30	.980	3.418	-.768	3.331	2.265	6560
NCARPCM1	.980	2.443	-.115	2.440	2.115	6560
UKHADCM3	.975	2.116	-.370	2.084	1.723	6560
UKHADGEM	.987	1.772	.223	1.758	1.407	6560
MODBAR	.982	1.704	-.421	1.652	2.410	6560

These results show that almost all models are very good at simulating the spatial pattern of annual MSLP – pattern correlations (except for the IPSL model) range from 0.908 to 0.987. There are, however, small biases in MSLP with most models biased slightly low. The exception to this “small bias” result is GISS-EH which has a large negative bias (although the overall pattern is relatively good, r = 0.935).

EXAMPLE 3:

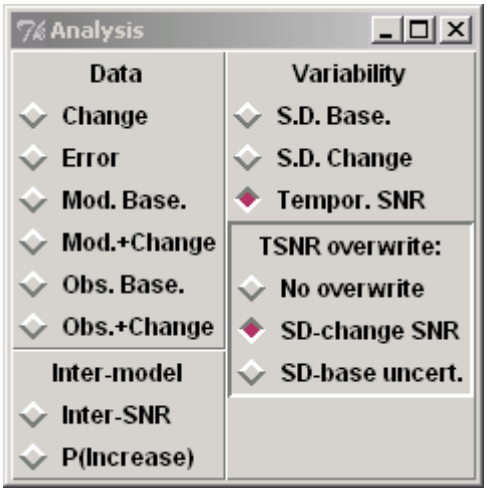
For the third example we consider **changes in variability** (expressed in SCENGEN in terms of percentage changes in inter-annual standard deviation, s.d.). We will do this using the average of all models except FGOALS and GISS-ER. We will also examine uncertainties in both the model baseline s.d. values and in changes in s.d..

First, minimize or close any existing maps and select "Globe" again as the study region. Next, on the Analysis window, select "S.D. Change". Then, on the Models window (if necessary) select "All" and then de-select FGOALS and GISS-ER. Finally, select precipitation again on the "Variable" window. Note that the season (annual) is not changed. Also, the "Warming" window has not been changed, so we are still considering the A1T emissions scenario with default MAGICC settings, and the year 2063 when the amount of global-mean warming is 2°C. Now click on RUN, and the map below will be displayed.

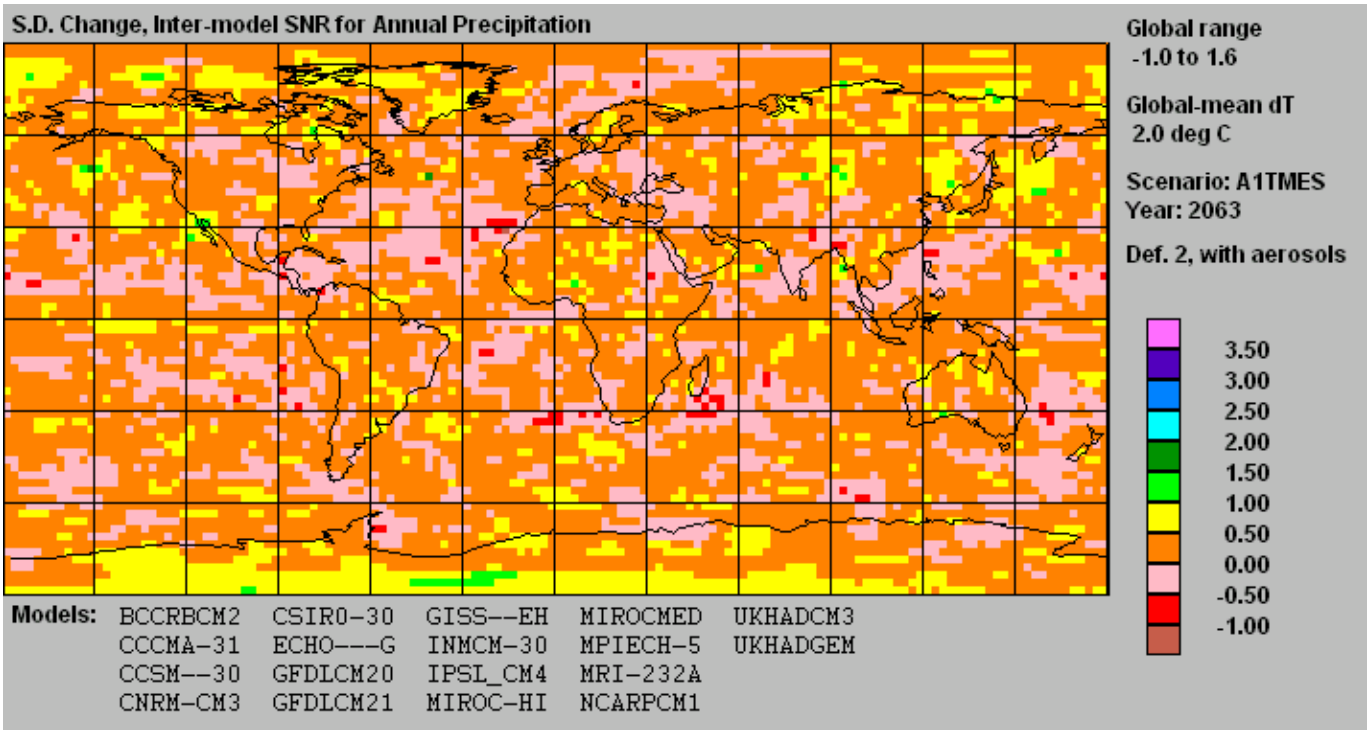


This is an extremely noisy pattern of change, suggesting that there is considerable uncertainty in projections of variability change for precipitation – as we will show more clearly below. On average, changes in variability are small even for a global-mean warming of 2°C – most of the map has changes of magnitude less than 20%. This does not mean, however, that individual models all show small changes in variability (a fact that the user can easily verify by selecting individual models). Rather, the low variability changes arise from the fact that different models give quite different results for the patterns of change in annual precipitation variability, and the individual extremes tend to cancel out.

To obtain a better idea of the uncertainty in variability projections we can look at the inter-model signal-to-noise ratio for s.d. changes (SD-change SNR). SD-change SNR is the above model-mean pattern of change in s.d. divided by the pattern of inter-model standard deviations of s.d. change, a dimensionless quantity. To display SD-change SNR, one must first click on Temporal SNR on the “Analysis” window, and then on “SD-change SNR” in the TSNR panel, as below ...

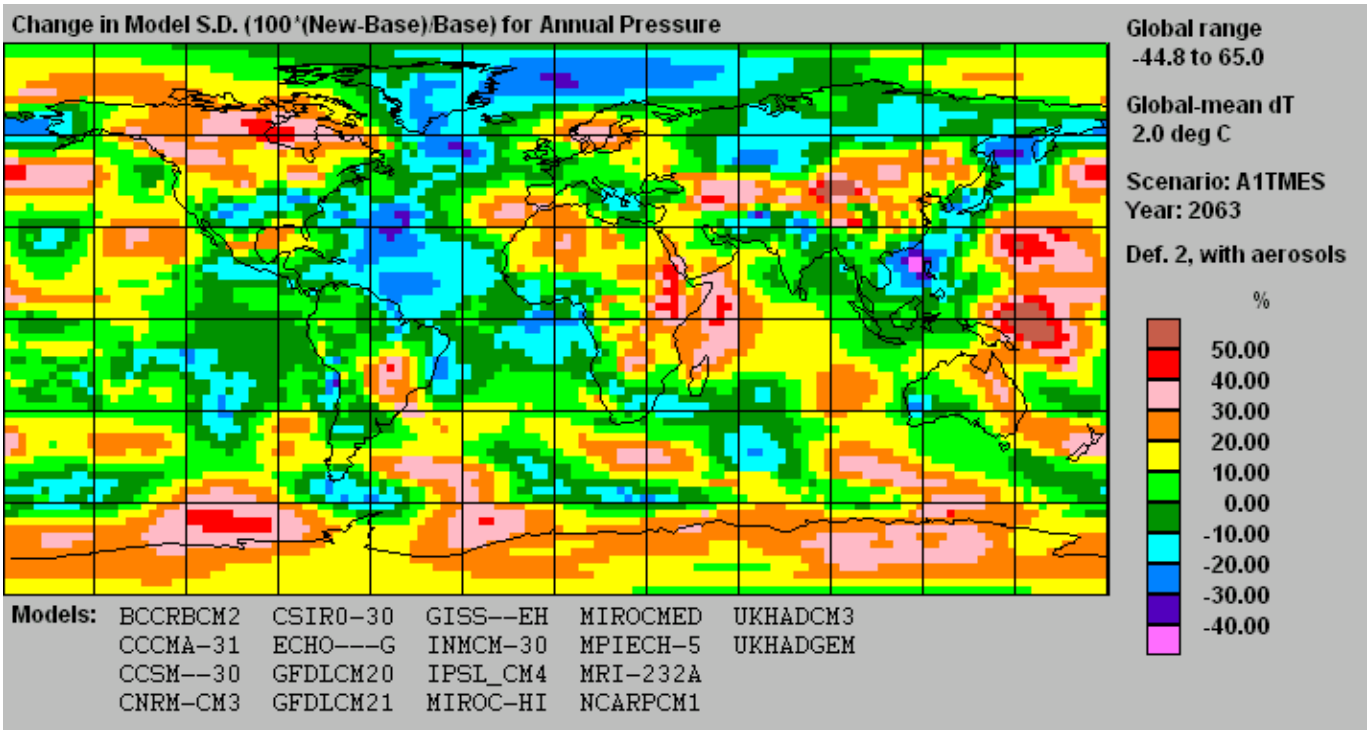


This gives …

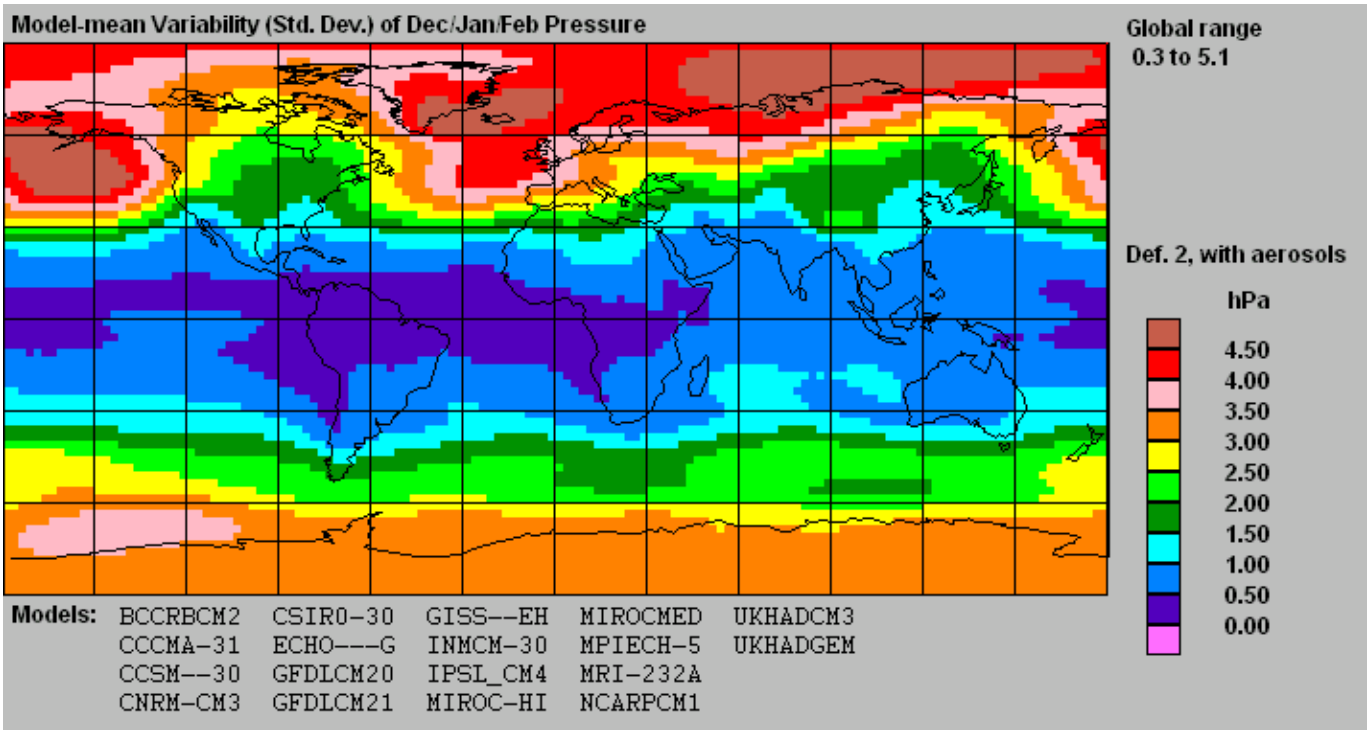


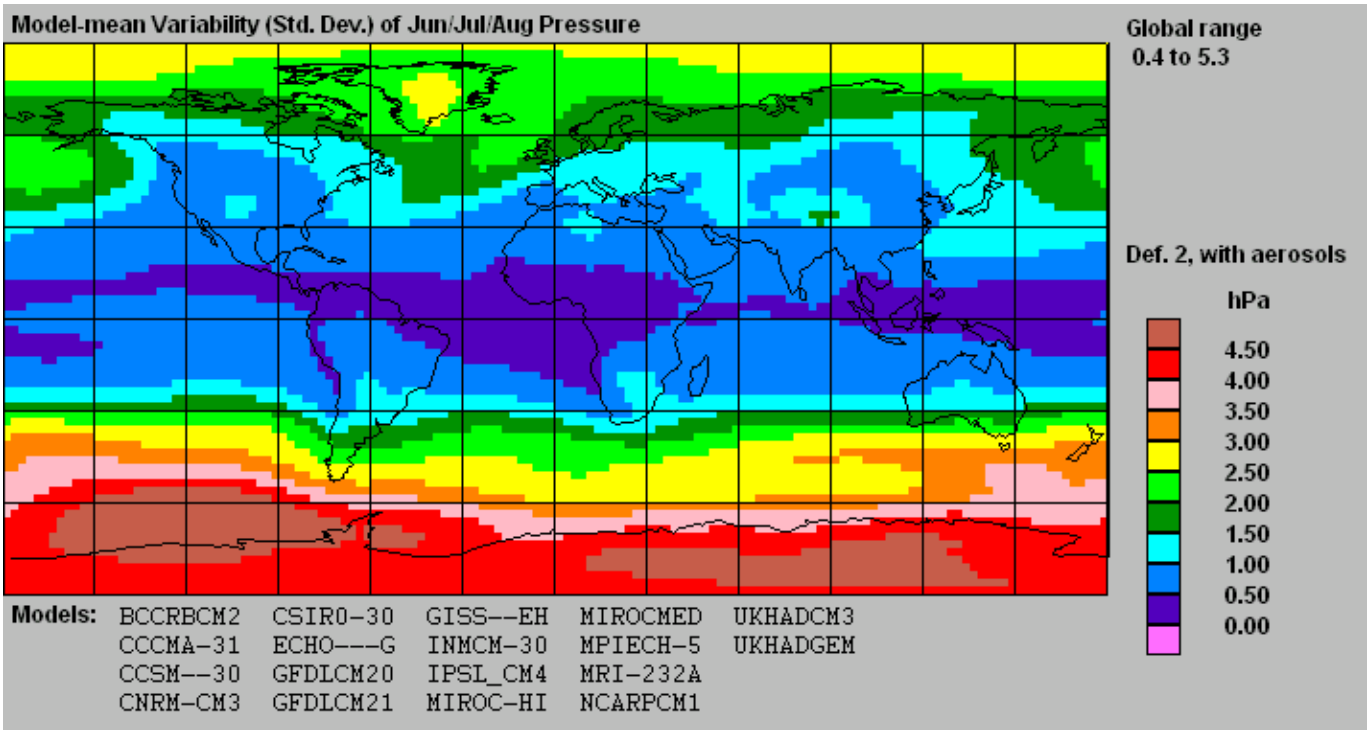
Note that almost all the map is either pink or orange, showing that, virtually everywhere, the inter-model SNR for s.d. changes is less than 0.5 in magnitude. In other words, the model-mean signal for s.d. change is generally less than half the inter-model variability in these projected changes. This implies that, for annual precipitation, one can have little confidence in model-projected changes in s.d.

Not all variables have such noisy and uncertain patterns of change as precipitation. As another example we consider changes in pressure (MSLP) variability. To do this, first click on “No overwrite” in the TSNR panel of the Analysis window to de-select SD-change SNR. Then click on the S.D. change button in the Variability window. Then click on Pressure in the Variable window; then on RUN. This will give …



How does one interpret this result? First, it would be more appropriate to look at seasonal variability changes, as annual changes may reflect either compensating or additive seasonal changes. In this case, seasonal changes show similar results to those for the annual case. One might then speculate that mid to high latitude changes in MSLP variability are associated with changes in storm tracks, while low latitude changes reflect changes in ENSO variability. Some support for this comes from examining baseline variability (S.D. Base). Results for Northern Hemisphere and Southern Hemisphere winter (DJF and JJA) are shown below (where the Min/Max contour option has been chosen for clarity) …

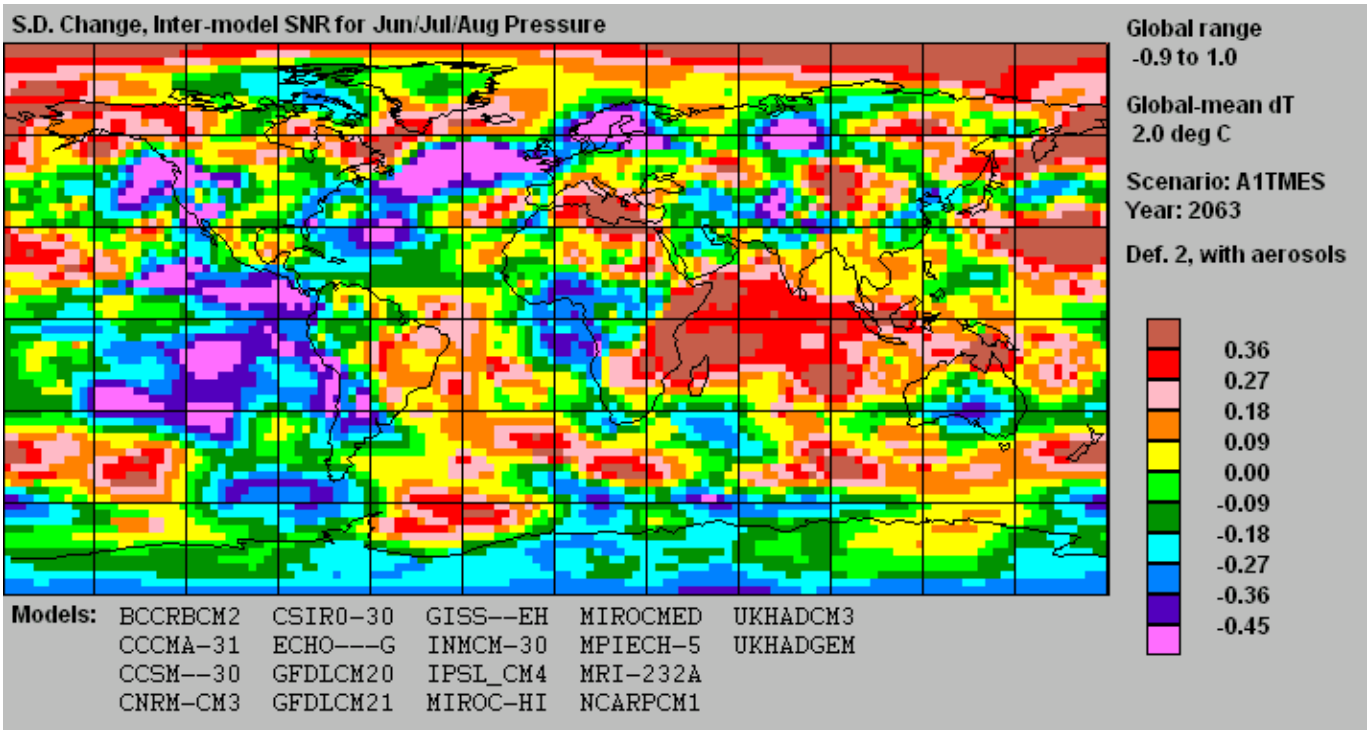


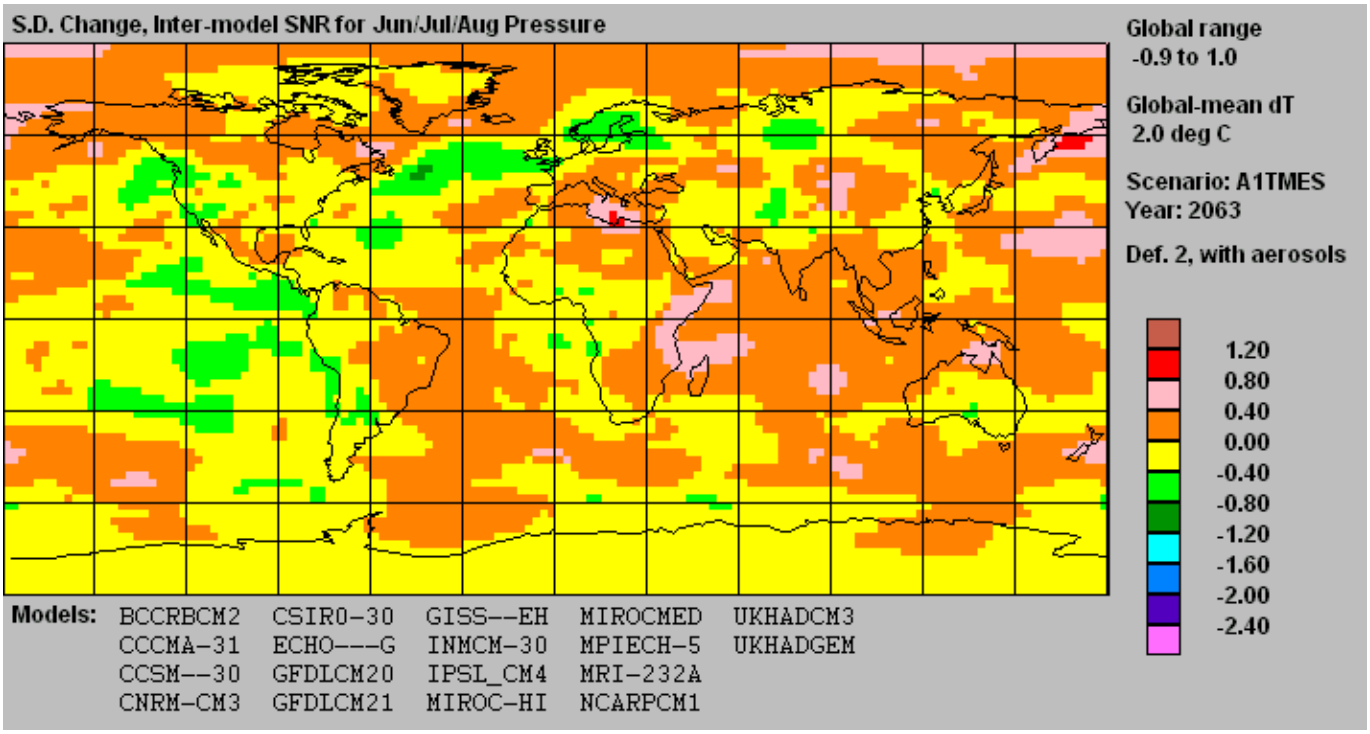


Highest variability areas are along the model winter storm track paths. In spite of the existence of ENSO variability, inter-annual variability in MSLP is very low in tropical regions.

This example, however, is given as a warning against speculative interpretations of results in the analysis of climate change. Prior to speculation, one should first ask whether the changes found are statistically meaningful. In this case we can do this by looking at the SD-change SNR results, shown below. Note that you have to first click on “Tempor. SNR” in the Analysis window

before “SD-change SNR” can be selected. Note also that the Min/Max contour interval option is probably still selected. We show this result, together (below it) with the Default contour option result (which is less noisy).

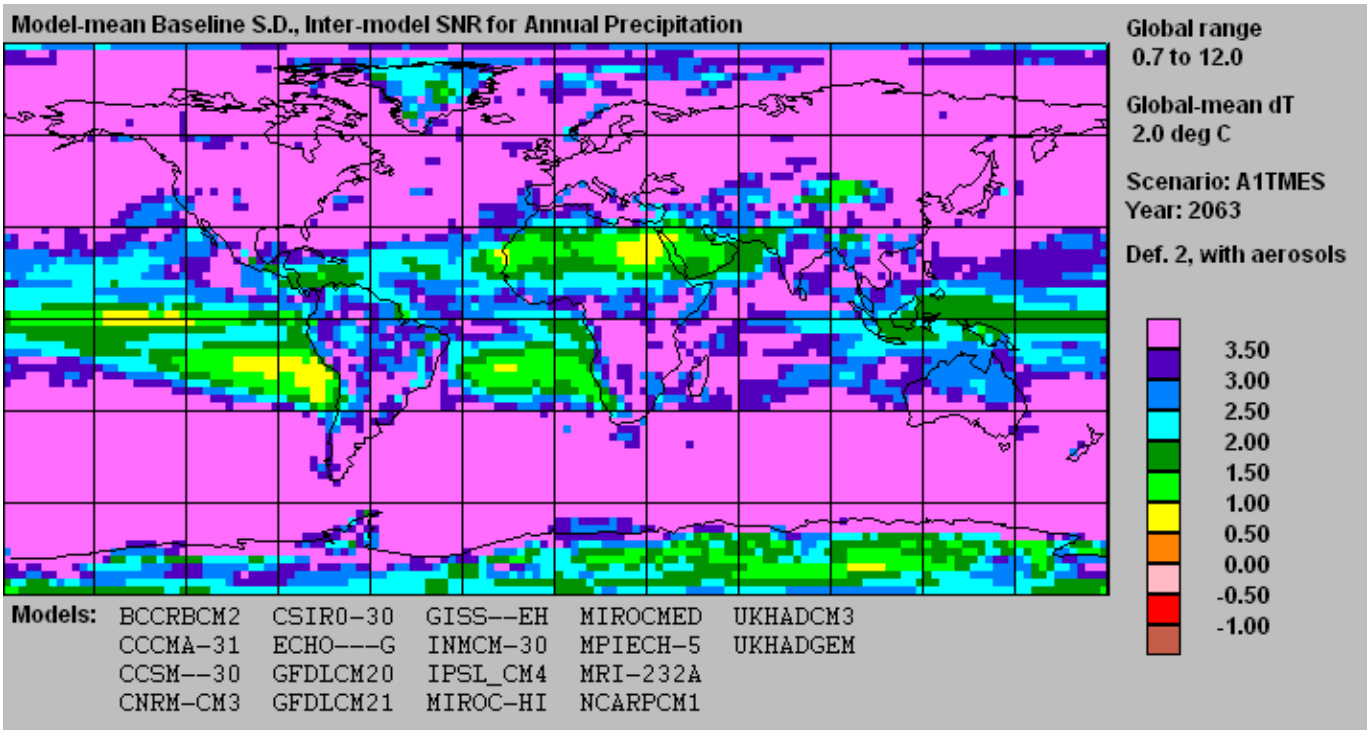




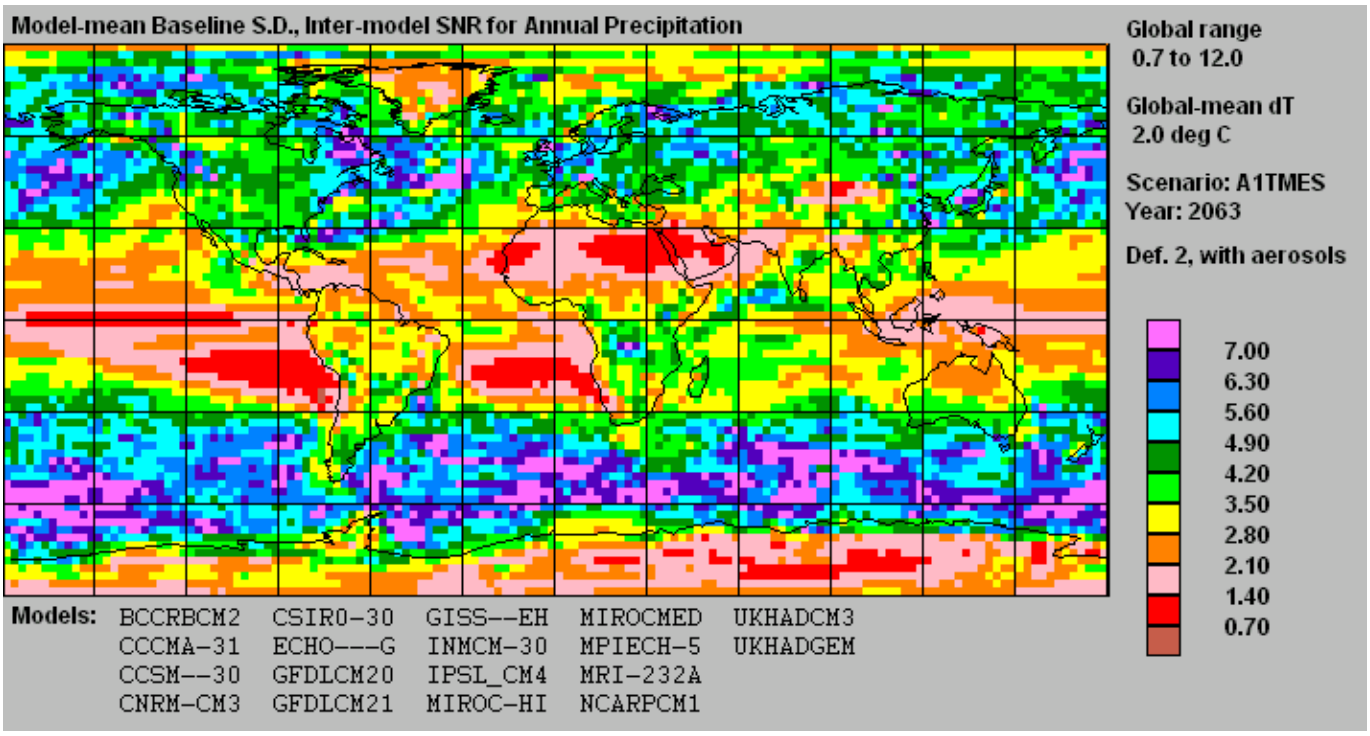
From this it can be seen that the projected model-mean s.d. changes are relatively small compared with inter-model differences in these changes – over most of the globe the SNR results are less than 0.4 in magnitude, indicating that the model-mean changes in annual MSLP variability are substantially less than the inter-model variability of these changes. This does not mean that there will not be any changes associated, for example, with movements in storm tracks – it simply means that any such model-predicted changes must be highly uncertain.

We now return to the precipitation results by re-selecting annual precipitation in the “Variable” window and “S.D. Change” in the “Analysis” window. The map for these changes is given above, where we noted that it was spatially very noisy. It is of interest to look at some of the other diagnostics for variability, which are given in the ENGINE/SDOUT directory. In SDCORRS.OUT, the inter-model pattern correlations for normalized variability change fields are given for the selected models, variable and season: in this case, 18 models, and annual precipitation variability changes. These pattern correlations range between –0.082 and +0.168. This confirms the above statement: for precipitation-variability-change fields, namely that models show very little agreement. By implication, one should be very circumspect in accepting any model results for changes in precipitation variability.

Although variability changes differ markedly from model to model, models are more consistent in their simulations of baseline variability. This can be seen by clicking on “SD-base uncert.” in the “Analysis” window. This gives an SNR for model baseline s.d., defined as the baseline grid point s.d. divided by the inter-model standard deviation of baseline s.d. values. The map below, which uses the default contour option, shows these SNRs …



One can see that large areas of the map have SNR values above 2. Using the Min/Max contour option shows the lower SNR regions more clearly.



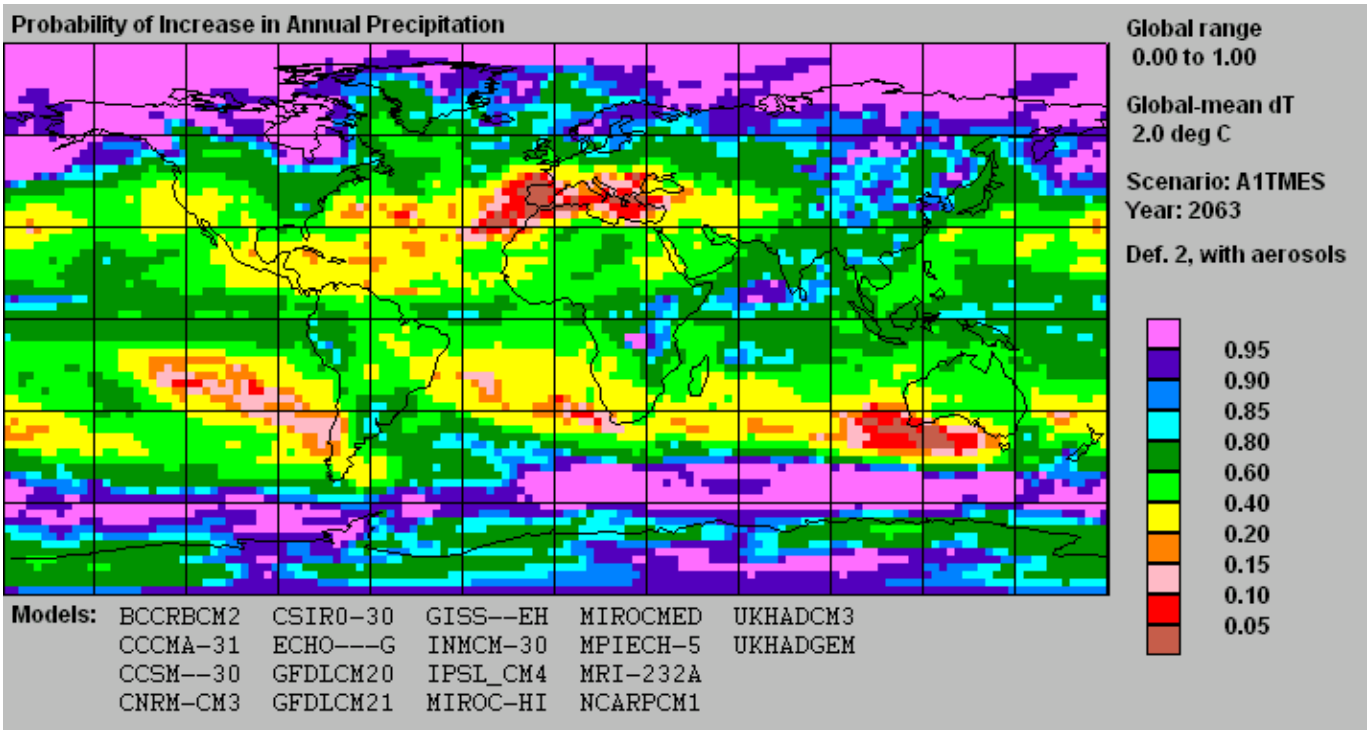
Low SNR values occur primarily in low latitudes, reflecting inter-model differences in baseline variability – in turn probably associated with inter-model differences in simulations of ENSO. There are also low SNR values over Antarctica. This must reflect inter-model differences in baseline s.d. values in this region.

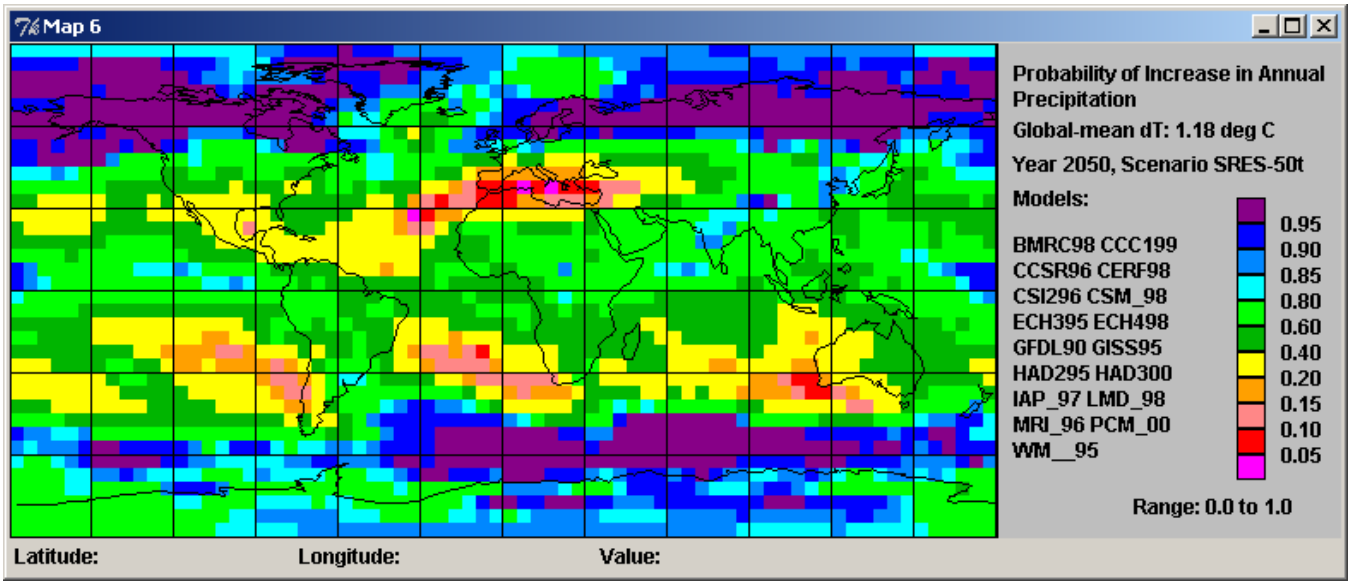
EXAMPLE 4:

For our final example we consider the **probability of an increase in annual precipitation**.

First, minimize or close existing maps. Next, select “P(increase)” in the “Analysis” window – and then click on RUN. The previous variable and model selections (annual precipitation, 18 models) will be retained. Note that for this type of analysis a number of models must be selected, since the probability of an increase is determined by comparing the model-mean change with the inter-model standard deviation.

The output map is displayed below (note the nonlinear contour interval) using the default contour interval option, together with the corresponding map from MAGICC/SCENGEN 4.1 …..





Regions with P>0.9 indicate a high probability of an increase in precipitation, restricted to the mid to high latitudes of both hemispheres. Regions with P<0.1 indicate a high probability of a precipitation decrease. These regions are restricted mainly to the subtropical highs, where precipitation is already low. Two other notable regions of likely precipitation decrease are the Mediterranean Basin and the southern (particularly southwestern) part of Australia. Note that these same regions of likely precipitation increases or decreases were also identified in version 4.1 using the previous generation of AOGCMs

A statistician might claim that the only significant results were where P>0.95 or P<0.05. From a practical point of view, however, the probabilistic results generated by SCENGEN are much more valuable. As an example, consider the western coastal regions of the USA. Over much of this region the probability of a precipitation increase is in the range 0.2 to 0.4. (Specific values can be seen below the map by moving the cursor over the gridbox of interest.) What this means is that a precipitation decrease is up to four times more likely than a precipitation increase, based on all 18 selected models. Policy makers are often perplexed by the large differences between individual model climate-change results at the regional level (and, hence, large uncertainties in any projections). How does one respond to this degree of uncertainty? Even with these uncertainties, as the above results show, there can be clear differences between the probability of a wetter (or drier) future climate compared with the probability of a change in the other direction. Information like this can help to decide which way the slant adaptation measures and define adaptation strategies that are more robust to uncertainties.

6. Choosing AOGCMs:

For many applications of MAGICC/SCENGEN it is useful to consider, not just a single model, or a set of single models, but the average over a number of models. This is an idea first introduced by Santer et al. (1990). Other researchers have used multi-model averages subsequently, but they have almost invariably failed to realize the power of averaging normalized changes (i.e., changes per unit global-mean warming) rather than raw changes. Use of raw changes has the serious disadvantage of weighting models with high climate sensitivity more than models with lower sensitivity. Use of normalized changes on the other hand has the advantage of factoring out uncertainties in the climate sensitivity, allowing these to be considered separately.

If a model average is to be used, then the question arises as to whether this should be a weighted or unweighted average – and, if weighted, how to choose the weights (see, e.g., Giorgi and Mearns, 2002; Tebaldi et al., 2004). Giorgi and Mearns (2002) have proposed that weights should reflect both model skill in simulating present-day climate and convergence of a model's projections to the multi-model average. There are, however, different ways to quantify these criteria.

For skill, there are considerable uncertainties in quantifying skill (see, e.g., Gleckler et al., 2008). We give a specific method below. For the convergence criterion, all published work on this has used raw model data, so that inter-model differences must reflect both differences in the climate sensitivity and differences in the underlying (normalized) patterns of change. The method that MAGICC/SCENGEN uses separates out these two factors. Given these problems, we are skeptical of the value of using weighted averages, but agree that the skill and convergence criteria can be useful in selecting a subset of models to average. We also consider that the use of convergence based on raw rather than normalized data is conceptually flawed. The approach recommended here is to use unweighted averages of normalized data from a subset of models (achieved using SCENGEN), and then to scale up the average using an independent estimate of global-mean temperature change (based on MAGICC). To average raw model data is clearly flawed since this will weight models by their sensitivity – and there is no reason to expect model skill to be related to climate sensitivity.

The justifications for use of a multi-model average are two-fold. First, as has already been demonstrated, multi-model averages are less spatially noisy. Second, by many measures of skill, multi-model averages are often better than any individual model at simulating present-day climate (as will be demonstrated below). As implied above, however, whether skill at simulating present-day climate translates to prediction skill is still an unresolved issue.

As an alternative to weighting models by some skill and/or convergence factor, we can use just a subset of models based on an assessment of skill – effectively restricting the weights to 1.0 and 0.0. In VALIDN.OUT, SCENGEN gives five statistics for model evaluation, calculated by comparing observed and present-day model control-run or 20^{th}-century run data for temperature, precipitation and pressure. The statistics may be calculated by month, season or annually, over the whole globe or over any user-selected region.

In the present example we will consider a case where we are using model results for impact studies over the continental USA (i.e., excluding Hawaii and Alaska). For this case we use both global statistics and statistics calculated over the continental USA region. As a validation

variable we use annual precipitation. Precipitation is more difficult to model than temperature and models do less well in simulating precipitation than temperature, so using precipitation is a stringent test of model skill. There is some value in looking at skill in simulating pressure (which is a direct indicator of atmospheric circulation), but one must be careful to restrict the validation region(s) to ocean areas – because of issues related to reduction to sea level already noted. For estimates of future change at a specific site, one might also consider model skill evaluated over a small study region surrounding the site. This is inherently less useful than assessing skill over a larger region because it is possible that a particular model may perform well over a relatively small region partly or even largely by chance.

The statistics used are: pattern correlation (r), root-mean-square error (RMSE), bias (B), and a bias-corrected RMSE (RMSE-corr). (VALIDN.OUT also gives results for the RK (Reichler and Kim, 2008) index, but we will not consider these here.) All statistics used here are those that employ cosine weighting to account for the changing area of grid boxes with latitude.

Bias is simply the difference, model minus observed, averaged over the chosen validation region. Of these four statistics, bias is probably the least important, since it is generally thought that biased models can still produce good information regarding future change, provided the bias is not too large. Bias may reflect incorrect baseline forcing (i.e., atmospheric composition and/or loadings of radiatively important species), rather than a problem with model physics. Bias, however, can affect RMSE, which is why RMSE-corr results are given as a text statistic. RMSE-corr is the root-mean-square error after a correction is applied to the model-mean field to remove any bias. It is related to RMSE by

$$(\text{RMSE-corr})^2 = (\text{RMSE})^2 - B^2$$

Table 6 shows these statistics for all models in the SCENGEN data base. To rank models I have used a semi-quantitative skill score that rewards relatively good models and penalizes relatively bad models. Each model gets a score of +1 if it is in the top seven (top third approximately) for any statistic over the globe or over the USA, and a score of –1 if it is in the bottom seven. The maximum skill score is therefore +8, which would mean that the model was in the top seven for all four statistics over both regions. The worst possible score is –8. In Table 6, models are listed in order of their skill scores. Other skill scores could be devised – but the results for others that I have considered are similar.

Once the models have been ranked, a subjective choice must be made as to which models to retain for multi-model averaging. In the present case, for example, based on the results in Table 6, one might chose the eight highest scoring models (a total of nine because two models are ranked equal eighth).

Table 6: ***Validation statistics used for ranking models.*** *The variable used for ranking is annual precipitation. The first numbers in each column are for the globe, while the second numbers are for the continental USA. The top three models for each case are shown in bold red type, while the worst three models in each case are shown in bold blue type.*

RANK (score)	FLUX ADJ?	MODEL	Pattern correlation	RMSE (mm/day)	Bias (mm/day)	RMSE-corr (mm/day)
1 (+8)	Yes	CCCMA3.1(T47)	**0.888**/0.836	**0.949**/**0.547**	**-0.010**/**+0.079**	**0.949**/0.541
1 (+8)	Yes	MRI-2.3.2	**0.886**/**0.909**	**0.967**/**0.438**	**-0.084**/**+0.033**	**0.963**/**0.437**
1 (+8)	Yes	ECHO-G	**0.910**/0.840	**0.864**/**0.609**	+0.128/+0.290	**0.854**/0.535
4 (+3)		HadCM3	0.858/**0.916**	1.256/0.711	+0.230/**+0.590**	1.235/**0.397**
4 (+3)		MIROC3.2med	0.833/0.687	1.162/0.802	**+0.035**/+0.279	1.162/0.752
6 (+2)		GFDL2.0	0.868/0.773	1.099/0.938	+0.091/**+0.693**	1.095/0.632
6 (+2)		GFDL2.1	0.857/0.789	1.149/0.784	+0.215/+0.497	1.128/0.606
8 (+1)		CCSM3	0.797/0.777	1.327/0.627	+0.160/**+0.079**	1.317/0.622
8 (+1)		IPSL4	0.808/0.752	1.269/0.783	-0.090/+0.384	1.266/0.682
10 (-1)		ECHAM5	0.808/**0.887**	1.351/0.742	+0.247/+0.569	1.328/**0.476**
10 (-1)		HadGEM1	0.797/0.851	**1.614**/0.681	**+0.385**/+0.312	**1.568**/0.605
10 (-1)		CSIRO3.0	0.814/0.588	1.209/0.875	-0.161/+0.288	1.198/0.826
10 (-1)		GISS-ER	0.774/0.795	1.430/0.723	+0.297/+0.406	1.399/0.598
14 (-3)		BCCR	0.793/0.684	1.311/0.741	+0.307/+0.108	1.275/0.733
15 (-4)		FGOALS-g1.0	0.816/**0.441**	1.226/**1.096**	+0.307/+0.512	1.187/**0.969**
15 (-4)		MIROC3.2hi	0.800/0.650	1.340/**1.110**	+0.281/**+0.740**	1.311/0.827
15 (-4)		GISS-EH	**0.733**/0.726	1.512/0.766	+0.340/+0.338	1.473/0.688
18 (-5)	Yes	INM3.0	**0.700**/**0.456**	**1.606**/**0.982**	+0.116/+0.381	**1.590**/**0.905**
19 (-6)		CNRM3	0.772/0.761	1.438/0.843	**+0.540**/+0.532	1.333/0.654
20 (-7)		PCM	**0.665**/**0.474**	**1.715**/0.935	**+0.343**/+0.328	**1.680**/**0.875**
Mean		5 best models	0.938/0.885	0.713/0.531	+0.060/+0.254	0.710/0.467
Mean		9 best models	0.924/0.860	0.787/0.602	+0.075/+0.325	0.783/0.507
Mean		All 20 models	0.910/0.843	0.870/0.655	+0.184/+0.372	0.850/0.539

Note the clear superiority of the first three models – but note also that these three models are all flux adjusted (see Randall and Wood, 2007). This gives them an advantage in a model validation exercise. Flux adjustment is not thought to be an issue for future climate change projections (see, e.g., Gregory and Mitchell, 1997). In other words, projections for a given model do not depend significantly on whether the model is flux adjusted or not. However, if a flux adjusted model validates well against present climate, this may not be a good indicator of model quality. In these cases, some other indicator of model quality should also be considered. In SCENGEN we give a model outlier analysis to help here – see below.

Note also that models that perform well in terms of global statistics generally perform well over the much smaller USA region. Models with high regional bias, however, need not perform poorly with the other statistics – HadCM3 and GFDL2.0 are examples.

As noted above, one reason for employing multi-model means is because model-average results are generally superior to almost all individual models implying the existence of unrelated

errors in the different models that cancel out to some extent. For example, for global pattern correlations, the 5- and 9-model averages are better than all individual models. For the USA region, however, there are three models (HadCM3, MRI and ECHAM5) that are better than the 5-model and 9-model averages, and four models (these three plus HadGEM1) that are better than the 20-model average. Although the results for the 5-model average are better than the 9-model average, the latter is likely to be more robust and allows a better assessment of inter-model variability. It also puts less weight on the flux-adjusted models.

In selecting models it is also useful to look at results in OUTLIERS.OUT. This is a way of factoring in the convergence criterion proposed by Giorgi and Mearns (2002). You should note that the above analysis uses all 20 models, yet it has already been noted that FGOALS and GISS-ER should probably not be used. In terms of validation statistics for annual precipitation, these are clearly not the worst models. We reject FGOALS primarily because this is the recommendation of the developers of this model. The model itself has known flaws. For GISS-ER, part of the reason for its rejection is because its projections differ radically (in terms of spatial patterns of change) from all other models – as can be seen on the OUTLIERS Table below (where models selected on the basis of skill are highlighted in red). The OUTLIERS Table also shows PCM as an outlier for annual precipitation change. PCM would also be rejected on the basis of its precipitation validation performance (although it should be noted that PCM performs better for other variables).

Based on convergence, the four “worst” models have already been rejected for their poor validation performance. It is interesting that the next worst model based on convergence (ECHO) is equal best in terms of skill.

We recommend using model average results here, but do not recommend any firm rules for selecting which models to average. The example here is meant to give users an idea of what factors should be considered. Some practitioners have suggested that all available models should be used and a weighted average employed. (In our case, selecting a subset of models is equivalent to giving weights of 1 or 0.) Giorgi and Mearns (2002) propose a weighting scheme based on skill and convergence criteria (the factors used here for model selection). With such a weighting scheme, ECHO would get a high weight based on skill, but a low weight based on convergence. Here, in this example, we would simply reject not using ECHO results.

If a skill-convergence weighting scheme were used for the nine models selected above on the basis of skill alone, the difference between the weighted and unweighted patterns of change is very small – and well within the uncertainties in any regional-scale projection of change. There is little to be gained in using a sophisticated weighting scheme.

In the OUTLIERS Table below, the analysis uses normalized percentage changes in precipitation rather than absolute changes. If ‘n’ models are being considered, the normalized percentage changes for model ‘i’ are compared with the average changes over all n-1 remaining models.

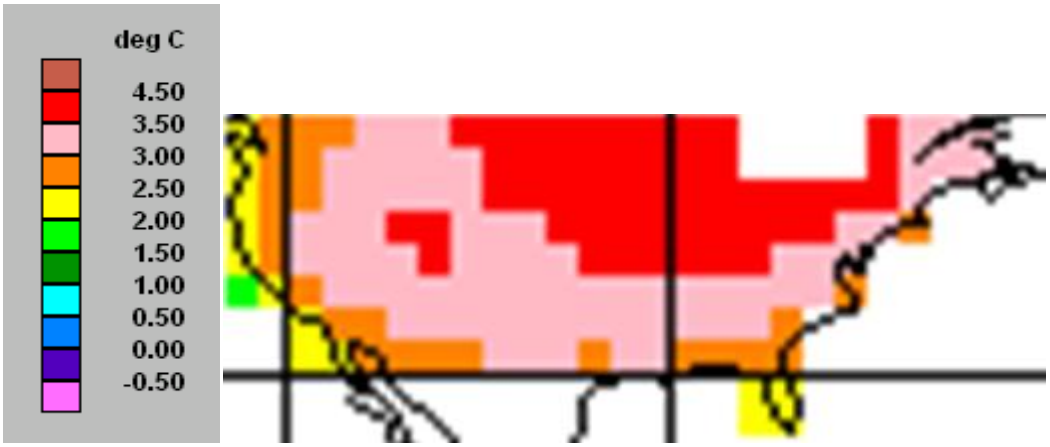
*** 20 MODELS : VARIABLE = CMAP PRECIP : SEASON = ANN : REGION GLOBE ***

MODEL OUTLIER ANALYSIS:
  COMPARING MODEL-i NORMALIZED CHANGE WITH AVERAGE OF REMAINING MODELS

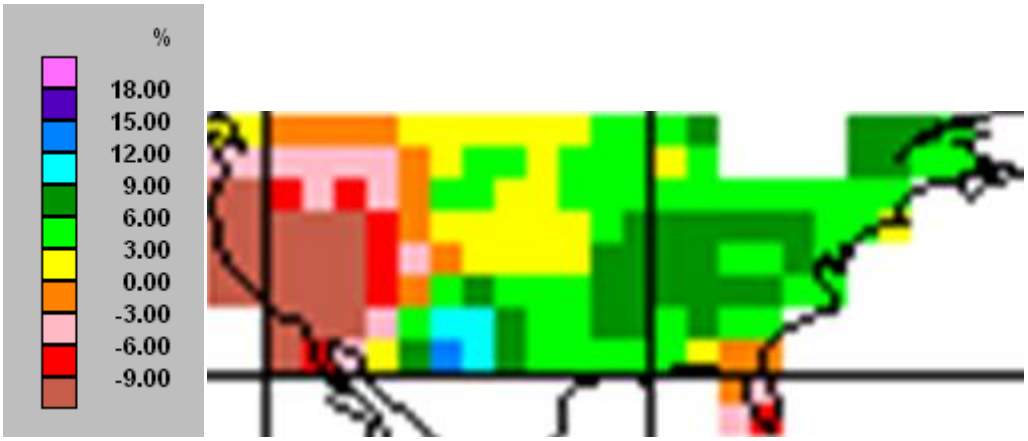
COSINE WEIGHTED STATISTICS

MODEL	CORREL(rank)	RMSE %	BIAS %	CORR-RMSE %	NUM PTS
BCCRBCM2	.480(6)	6.873	.515	6.854	10368
CCCMA-31	.608(1)	5.737	-.074	5.736	10368
CCSM--30	.319(15)	8.810	1.093	8.742	10368
CNRM-CM3	.260(18)	8.243	.271	8.239	10368
CSIR0-30	.291(17)	9.548	.709	9.521	10368
ECHO---G	.293(16)	8.709	-.759	8.676	10368
FGOALS1G	.513(4)	8.647	-1.145	8.571	10368
GFDLCM20	.424(7)	10.307	.604	10.289	10368
GFDLCM21	.414(9)	11.107	-2.058	10.914	10364
GISS--EH	.394(12)	7.895	.609	7.871	10368
GISS--ER	.124(19)	24.100	.245	24.099	10300
INMCM-30	.408(10)	7.166	.274	7.161	10368
IPSL_CM4	.422(8)	10.000	-.983	9.952	10358
MIROC-HI	.497(5)	5.665	.632	5.630	10368
MIROCMED	.588(2)	5.700	-.121	5.699	10368
MPIECH-5	.350(14)	15.456	.960	15.426	10361
MRI-232A	.369(13)	10.679	.353	10.673	10363
NCARPCM1	-.099(20)	15.363	.914	15.336	10368
UKHADCM3	.404(11)	10.149	-.838	10.114	10368
UKHADGEM	.525(3)	6.513	-.021	6.513	10368

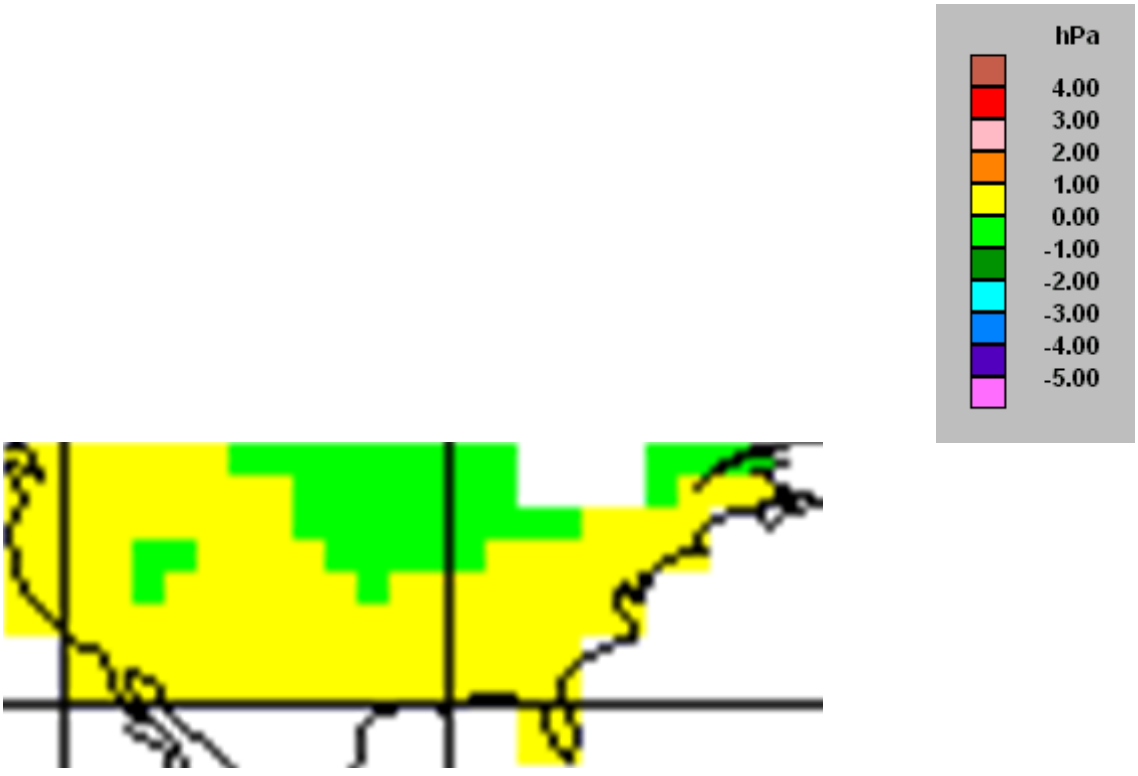
We now consider a specific example that makes use of these results, future changes in annual-mean temperature, precipitation and MSLP under the A1T-MES scenario at a time when global-mean warming for central MAGICC model parameters is 2°C (viz. for the 30-year interval centered on 2063). Results using the 9-model average are shown below. We have selected "USA" as a specific region.



Change in annual-mean temperature for 2°C global-mean warming, averaged over the 9 "best" AOGCMs. These results are based on the A1T-MES emissions scenario and include aerosol effects.



Change in annual-mean precipitation for 2°C global-mean warming, averaged over the 9 "best" AOGCMs. These results are based on the A1T-MES emissions scenario and include aerosol effects.



Change in annual-mean MSLP for 2^{o}C global-mean warming, averaged over the 9 "best" AOGCMs. These results are based on the A1T-MES emissions scenario and include aerosol effects.

Appendix 1: Halocarbons

MAGICC includes the following 30 halocarbons ...

CFC11, CFC12, CFC13, CF_4, CFC113, CFC114, CFC115, C_2F_6, CCl_4,$CHCl_3$, CH_2Cl_2, MCF, Ha1211, Ha1301, HCFC22, HCFC123, CH_3Br, HFC141b, HFC142b, HFC125, HFC134a, Ha2402, HFC23, HFC32, HFC43-10, HFC143a, HFC227ea, HFC245ca, C_4F_{10}, SF_6

In the input emissions files, only the 8 most important can be specified. These are ...

CF_4, C_2F_6, HFC125, HFC134a, HFC143a, HFC227ea, HFC245ca, SF_6

The other 22 gases are divided into two groups, gases controlled under the Montreal Protocol and all other gases.

Montreal gases (CFC11, CFC12, HCFC22, etc.) have fixed future emissions, controlled by the Protocol. The concentrations and forcings for these are hard wired into the code. For the other gases the emissions vary according to the SRES scenario, but the differences between the scenarios are small. Most inter-scenario differences in halocarbon forcing arise through differences in the emissions of the above 8 gases. MAGICC therefore uses an average total radiative forcing for the other gases, again hard wired into the code. The forcing error in doing this is tiny -- a few thousandths of a W/m^2 in 2100.

Appendix2: CO_2 concentration stabilization:

The emissions scenarios in the MAGICC emissions scenario library that lead to concentration stabilization have been constructed specifically for the current (5.3) version of the code, using an inverse version of MAGICC. There are two sets of CO_2 concentration stabilization scenarios, labeled WRExxx and xxxNFB where xxx gives the stabilization level. The CO_2 concentration stabilization profiles used to define these emissions scenarios are based on and very similar to the set of WRE profiles originally published by Wigley et al. (1996). The WRExxx scenarios are to be used when climate feedbacks on the carbon cycle are operating (which is the normal situation), while the xxxNFB scenarios are to be used when these feedbacks are turned off (e.g. for scientific sensitivity studies). The concentration pathways in MAGICC 5.3 are almost exactly the same as in MAGICC 4.1. However, the emissions scenarios that produce these concentration profiles differ slightly, for reasons that are explained below.

In Wigley et al. (1996), concentration profiles stabilizing at 350, 450, 550, 650 and 750 ppm were given. These profiles were devised in a way that ensured that the implied emissions changes departed only slowly from a baseline no-climate-policy case (the IS92a scenario from Leggett et al, 1992). This "slow departure" assumption was a somewhat *ad hoc* way to account for the economic and technological challenges that are presented by mitigation, which make a rapid departure from a no-policy case virtually impossible. Although *ad hoc*, subsequent more sophisticated economic analyses have shown that the WRE pathways are close to optimum in a cost-effectiveness sense (i.e., they minimize mitigation costs over time).

These early analyses began with smooth concentration profiles and used a simple inverse carbon cycle model to calculate the emissions required to follow the prescribed concentration pathways. The inverse model used did not account for climate feedbacks on the carbon cycle – back in 1996 this was "state of the art". These climate feedbacks are, on balance, positive, leading, for any given emission scenario, to larger concentrations than would occur otherwise. The emissions required to follow a given concentration profile are therefore <u>less</u> than would otherwise occur. The emissions requirements given in the original paper are therefore overestimates – mitigation is tougher if climate feedbacks are accounted for.

Climate feedbacks make it more difficult to define an emissions scenario to match a specified concentration profile. This is because the emissions-concentration relationship depends on temperature and thus on the many factors that determine future temperature changes – the climate sensitivity and other climate model parameters, historical forcing estimates, and assumed future emissions of non-CO_2 gases.

MAGICC uses emissions as its primary input. So, to study concentration stabilization issues we need to determine specific emissions scenarios that will lead to concentrations that follow the WRE profiles. Climate feedbacks mean that the calculated emissions will be specific to a single set of climate model parameters and a single scenario for non-CO_2 gases. In MAGICC 4.1 we used best-estimate (i.e., TAR default) model parameters and historical forcings, and the P50 (SRES median) emissions scenario for non-CO_2 gases. Most importantly, the best-estimate sensitivity used in MAGICC 4.1 was 2.6^{o}C. With the new IPCC AR4 report, best-estimate model parameters and historical forcings have changed (with a new best-estimate sensitivity of 3.0^{o}C), so the stabilization emissions scenarios must be re-calculated. Furthermore, as noted above, we no longer use the P50 baseline for non-CO_2 gases, preferring a non-CO_2 scenario that is more consistent with CO_2 stabilization (the extended MiniCAM Level 2 scenario). The WRE concentration profiles will only be produced exactly if the same model parameters, historical

forcings, and future non-CO_2 emissions are used. (In fact, the concentration profiles are not produced precisely because of numerical rounding errors, but the differences are always less than 0.05 ppm.)

To determine the stabilization emissions scenarios that are in the MAGICC 5.3 data base we first use the P50 emissions scenario with default model parameters to determine the baseline (no-climate-policy) concentration profile. For 250 ppm to 750 ppm stabilization targets, this profile is followed for a period from 5 to 20 years (depending on the stabilization target) before concentrations depart as a consequence of mitigation. We then construct smoothly varying concentration profiles using the Padé approximant method as explained in Wigley (2000). The parameters used for fitting are given in the Table below.

Table A1*: Padé approximant fitting parameters*. *Y_0 is the year of departure from the baseline. Using 2005.5 as in the three lower concentration targets, which has already passed, is an idealization that retains closer similarity to the original WRE profiles. The effects on implied emissions are negligible. For 350 ppm stabilization, the original departure year (used also in MAGICC 4.1) was 2000.5. Y_1 and C_1 define the anchor points that the profiles are constrained to pass through. For 250 and 350 ppm stabilization, where the profiles necessarily overshoot the stabilization target, this is the point and value at which concentration maximizes. Y_{end} is the year at which concentration stabilizes. Note that the MAGICC 5.3 emissions library does not give the 250 and 1000 ppm stabilization cases.*

Target (ppm)	Y_0	C_0 (ppm)	$[dC/dt]_0$	Y_1	C_1 (ppm)	Y_{end}
250	2005.5	378.323	1.935	2040.5	414.0	2200.5
350	2005.5	378.323	1.935	2040.5	414.0	2150.5
450	2005.5	378.323	1.935	2050.5	440.0	2100.5
450 overshoot	2020.5	412.584	2.639	2090.5	540.0	2300.5
550	2010.5	388.546	2.154	2070.5	514.6	2150.5
650	2015.5	399.954	2.408	2090.5	589.4	2200.5
750	2020.5	412.584	2.639	2110.5	667.9	2250.5
1000	2050.5	514.098	4.092	2200.5	885.0	2375.5

Once the concentration profile is defined, we use the inverse version of the MAGICC code to determine the emissions required to follow the profile – essentially embedding the 5.3 climate model code in a iterative shell that marches through time, running the forward model over and over again with gradually changing emissions until each particular concentration level is reached at a specified accuracy level. When these emissions scenarios are run in forward mode with MAGICC, they reproduce the WRE concentration profiles with an error of less than 0.05 ppm.

In the original WRE analysis, and in MAGICC 4.1, the dates of departure from the baseline were mid-years of 2000 (for WRE350), 2005 (for WRE450), 2010 (for WRE550), 2015 (for WRE650) and 2020 (for WRE750). It is now 2008, so the departure date assumptions for WRE350 and WRE450 are already wrong. The difference for WRE450 is negligible, but it is significant for WRE350 where the concentrations in the stabilization profile out to 2008 are noticeably below those observed. (Concentrations are also below those in P50, but the differences are small.) To account for the WRE350 discrepancy we have devised new with-feedback and no-feedback

profiles that use 2005 as the departure date. In future it will probably become necessary to revise all of the departure dates.

Even with the initial concentrations and stabilization date and level specified, there is still a range of possible stabilization pathways. The WRE profiles were chosen to follow monotonic trajectories that approach the stabilization point from below along a smoothly varying path that leads also to smoothly varying emissions changes (which, as noted above, is impossible for the 250 and 350 ppm stabilization cases as we have already passed these targets). It is possible, however, that, even for higher concentration targets, a pathway may, for one reason or another, overshoot the target and then have to decline towards the chosen target. This might occur if it turns out to be impossible to develop and deploy carbon-neutral technologies sufficiently rapidly to follow a monotonic path (which is increasingly likely for lower stabilization targets), or because an initially chosen target is judged, at some later date, to be too high to avoid serious climate consequences. Overshoot profiles are discussed in more detail in Wigley et al. (2007).

To provide an example of the overshoot possibility, a single overshoot case has been added to the MAGICC emissions scenario library (450OVER) – overshoot to 540 ppm before declining to stabilization at 450 ppm, as used in Wigley (2006). In Wigley (2006), the assumed baseline was the A1B emissions scenario, and concentrations were assumed to follow A1B concentrations to 2020. The A1B scenario was also used for the emissions of non-CO_2 gases. Here, for consistency, we use P50 as the baseline for CO_2 concentrations, and the MiniCAM Level 2 scenario for non-CO_2 gases. The peak concentration of 540 ppm is assumed to occur in 2090, and stabilization at 450 ppm occurs in 2300.

A final important point is that some key parameters in the carbon cycle model in MAGICC 5.3 have been changed from those used in MAGICC 4.1. These changes make very little difference to the concentration projections for the six IPCC illustrative scenarios. They do, however, affect the magnitude of climate feedbacks on the carbon cycle. Both with-feedback and no-feedback results are consistent with the average results for the models used in the C4MIP intercomparison exercise (Friedlingstein et al., 2006). A comparison of MAGICC 5.3 results with those of the two other carbon cycle models used in the TAR is given below.

***Table A2**: Comparison of TAR carbon cycle model concentration projections (ppm) with MAGICC 5.3 projections. This is an update of results shown in Tables 7.1 and 7.2 of Wigley et al. (2007). For consistency with the TAR results, all concentrations are beginning-of-year values, and all simulations assume a climate sensitivity (ΔT2x) of 2.5°C. The models are those used in the IPCC TAR: Bern (Joos et al., 2001), and ISAM (Kheshgi and Jain, 2003)*

	2050			2100		
SCENARIO	Bern	ISAM	MAGICC 5.3	Bern	ISAM	MAGICC 5.3
A1B	522	532	529	703	717	707
A1T	496	501	497	575	582	569
A1FI	555	567	564	958	970	976
A2	522	532	529	836	856	852
B1	482	488	485	540	549	533
B2	473	478	473	611	621	612
IS92a	499	508	505	703	723	714
IS92a (NFB)			494	651	682	673
Feedback			11	52	41	41

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PRINTING TIPS

There is currently no built-in printing capability for SCENGEN, but it is easy to import the maps into other programs and print them from there.

To perform a screen-capture of a SCENGEN map window, simply click on the window and press Alt+Prnt Scrn. This copies an image of the window to the clipboard. You can then paste the image into a document in another program like Microsoft Word by typing CTRL+V. If you want to edit the image (to trim off borders or annotations, for example), one can paste it into a simple image editor like Microsoft Paint, which is typically found in the “Accessories” menu. An alternative is to use commercial software like “SnagIt”.

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Version 1, June 2008
Version 2, September 2008

The primary modification in Version 2 is to the section on sea level rise. Additional information about the carbon cycle model has been added, the Section on model selected has been modified with more information added on the OUTLIERS Table, and a new Appendix inserted giving information about how MAGICC handles halocarbons.

MAGICC/SCENGEN 5.3 DIRECTORY STRUCTURE